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Industrial output fluctuations in developing countries: General equilibrium consequences of agricultural productivity shocks

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Industrial Output Fluctuations in Developing Countries: General Equilibrium Consequences of Agricultural Productivity Shocks*

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Abstract

This paper shows that a negative shock to agricultural productivity may increase food prices, and labor and capital can move away from manufacturing into agriculture to meet the subsistence requirement for food. This effect depends on income levels and openness to trade. Using annual manufacturing data and rainfall shocks as the instrument for crop yields (proxy for agricultural productivity), I find that an exogenous decline in yield decreases manufacturing output as well as employment and capital investment in manufacturing. Overall, crop yield variation can explain up to 44% of industrial output fluctuations in developing countries (rainfall shocks cause 31% of the fluctuations). Lastly, this paper shows that such perverse phenomena, in which resources move toward the sector with declining productivity, can lead to a significant reduction in aggregate productivity.

JEL codes: F1, E32, O11; *Key words*: Economic Fluctuations, International Trade, Development, International Comparisons, Agriculture

1 Introduction

An important regularity in macroeconomic data is the frequent and large changes in developing country growth rates, compared to the relatively stable growth rates in developed countries (Lucas, 1988). Accordingly, many authors have focused on the negative relationship between aggregate output volatility, defined as the standard deviation of yearly output growth rates, and per capita income levels. The negative association between the

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two becomes stronger when manufacturing is considered separately, implying much higher industrial output volatility in poor countries.[1]

Higher industrial output volatility can have negative effects on both the level and the growth path of income.[2] Importantly, abrupt negative shocks to household incomes can be especially detrimental in developing countries, as their income levels often barely exceed the level of subsistence (Burgess, Deschenes, Donaldson, and Greenstone, 2013; Bhalotora, 2010; Maccini and Yang, 2009). Moreover, developing countries are less able to withstand income fluctuations due to their underdeveloped financial sectors and weaker coping and mitigating mechanisms. For these reasons, analyzing the causes of fluctuations is important, especially for developing countries.

This paper is part of a growing literature that studies year-to-year fluctuations of industrial output in less developed countries.[3] An important paper by Koren and Tenreyro (2007) decomposes volatility across countries, and shows that output is more volatile in poor countries mainly because they specialize in fewer and highly volatile sectors and are subject to larger country-specific shocks. In addition, many authors attempt to provide underlying mechanisms by relying on differences in the complexity of production process, differences in institutions, or differences in the risk content of exports and imports (e.g., Koren and Tenreyro, 2013; Krishna and Levchenko, 2012; Malik and Temple, 2009; Cunat and Melitz, 2012; Kraay and Ventura, 2007; Kose, 2002; Giovanni and Levchenko, 2011; Tapia, 2012). For example, Koren and Tenreyro (2013) theoretically show that firms in developed countries have diversification benefits from using a greater number of input varieties, lowering output volatility. Developing countries also tend to have poor institutional ability to enforce contracts, which may lead to a comparative advantage in less complex products that are associated with higher output volatility (Krishna and Levchenko, 2012).

In contrast, this paper focuses on the demand-side reasons to explain the volatility in industrial output. I use a prominent characteristic of developing economies – the large portion of income spent on food to satisfy subsistence needs – and show how agricultural shocks can generate large industrial output fluctuations through general equilibrium linkages. In the baseline model, the effects are stronger for lower income countries, because non-homothetic preferences magnify the consequences of falling agricultural yields in these countries. On the other hand, the volatility literature does not use non-homothetic preferences, only con-

[1]Regressing volatilities (over the period 1970-2002) on log per capita GDP and log population reveals that a 10% decrease in per capita GDP is associated with a 0.3 unit (30 percent of the total GDP) increase in industrial output volatility and a 0.07 unit increase in aggregate output volatility (see Table A.1).

[2]Van Wijnbergen (1984) notes that even a temporary decline in manufacturing can have a permanent negative impact on an economy, assuming that growth occurs through learning-by-doing technological progress. In addition, Ramey and Ramey (1991) argue that volatility can reduce mean output ex-post if producers have to make decisions on resources before realizations of shocks. Bernanke (1983) and Pindyck (1991) suggest that volatility can cause lower investments.

[3]More broadly, it belongs to the literature that studies determinants of output volatility. Giovanni and Levchenko (2009), Kose (2002), and Mendoza (1995) investigate the relationship between trade openness and output volatility. Recent studies tend to focus on the effect of firm-level idiosyncratic shocks on aggregate fluctuations (Gabaix, 2011; Giovanni and Levchenko, 2012; Giovanni et al., 2014).

tains manufacturing-type sectors in the models, and relies mainly on the size of shocks (e.g., productivity shocks and world price shocks) or different elasticities of factor supply (due to different institutions) to explain volatility levels across countries. Another very important departure from the previous literature is that I use a clearly observable source of shocks, rainfall shocks.[4] This allows me to measure the size of the shocks across countries as well as the actual response to the shocks on manufacturing.[5]

To develop the idea, I build a two-sector static general equilibrium model featuring Stone-Geary preferences with subsistence requirements for food. The baseline model assumes a closed economy, which can be partly justified by low agricultural trade volumes in the real world with high barriers to agricultural trade. In the model, a negative shock to agricultural productivity, such as a drought, causes food prices to rise. The expenditure on the subsistence requirement for food then rises, and there will be less income leftover for manufacturing. This leads poor households to shift consumption away from manufactures. On the production side, in order to meet the subsistence requirement in the face of the decreasing agricultural productivity, some labor and capital resources move away from manufacturing into agriculture, further reducing manufacturing output. Perversely, the economy shifts resources toward the sector with declining productivity, leading to a significant reduction in aggregate productivity. This effect becomes stronger the closer the country is to the subsistence level.

To understand the quantitative importance of the theoretical mechanisms, I calibrate the model using data on endowments, employment shares, and total output across countries. Time varying cross-country data on crop yield is used as a measure of agricultural productivity. The simulation results confirm that the model generates significantly higher volatility in poor countries in response to agricultural productivity shocks.

I turn to panel regressions to look for evidence of these effects in the data. I investigate whether a fall in crop yield leads to a fall in industrial output (excluding the sectors that use agricultural products as primary inputs), as predicted by the baseline model. However, yields and manufacturing output may co-move due to some factors outside the model. For example, an economy-wide rise in total factor productivity will boost productivity and output in all sectors. This generates a positive relationship between yields and manufacturing output. On the other hand, government policies that favor agriculture may attract labor and capital resources into agriculture and away from manufacturing. This could cause crop yields to rise and manufacturing output to decline, generating a negative correlation.

To address the endogeneity issue, I use cross-country panel data which includes 118 countries for the period 1970-2002, and regress changes in manufacturing output on changes in

[4] The previous literature rarely attempts to measure the size of shocks and econometrically estimate the response to the shocks that cause industrial output fluctuations. Instead, it focuses on variance decomposition, calibration, or estimating the relationship between the volatility and some country characteristics such as the complexity of products, trade openness, financial development, or policy variables.

[5] Burgess and Donaldson (2012) also use rainfall shocks in India to study volatility, but the implication is mainly associated with agriculture.

yield, employing rainfall shocks as the instrument for yields. I construct crop-area weighted rainfall using GIS (Geographic Information System) software, which has strong predictive power for crop yields in the first stage. In the second stage, I find that exogenous declines in yield cause significant reductions in manufacturing output in developing countries: a 10% decrease in yield can lead to a 3.1% decrease in manufacturing output. Overall, crop yield variation can explain up to 44% of industrial output fluctuations in developing countries (rainfall shocks through yields cause 31% of the fluctuations). On the other hand, consistent with the theory, I find that the effect disappears for higher-income countries. In addition, I find that the effect is larger when a country is less open to trade, when financial development is low, and when agriculture production as a share of GDP is large, which corroborates the theory.

Moreover, I find two main pieces of evidence for the model's key mechanism. First, I find that exogenous declines in crop yield result in significant declines in both employment and capital investment in manufacturing in developing countries. The labor reallocation channel is especially important, because developing countries are labor abundant and most industries are labor intensive. Importantly, I show that the labor reallocation effect is stronger for countries whose planting cycles are seasonal rather than year-round: a 10% decrease in yield can lead to a 3.5% decrease in manufacturing employment in northern-hemisphere countries. To illustrate, an agricultural worker in a northern-hemisphere country has an incentive to move to other sectors after the harvest in the fall, because there is not much work to do until the next harvest season. This evidence strongly supports the mechanism proposed by the theory. Second, using cross-country time-series data on annual crop prices, I find that domestic rainfall shocks significantly affect domestic food prices despite the existence of the world food market.[6]

Lastly, I turn back to the theory. I extend the baseline model and present two types of open-economy models to study how international trade may affect the prediction differently. First, in a two-country model, I demonstrate that the positive link between agricultural productivity and manufacturing output is attenuated in home country as the size of foreign country increases, and the link eventually changes sign (becoming a negative link).[7] Second, I build another open economy model in which foreign agricultural products are imperfect substitutes of home products, which allows imperfect pass-through of domestic productivity shocks to domestic food prices. I find that the direction of the closed economy results still holds, but the magnitudes of the effects are attenuated. Using these results, I show that trade openness may help mitigate the impact of agricultural shocks on aggregate output. This implication is in line with papers by Tombe (2015), Gollin and Rogerson (2014), Burgess and

[6]This finding is consistent with the literature showing that the domestic supply shock is the main contributing factor for short-run (changes within a year) food price fluctuations, while long-run price fluctuations are primarily attributed to international prices or exchange rates (Burgess, Deschenes, Donaldson, and Greenstone, 2013; Anderson and Nelgen, 2012; Loening et al., 2009).

[7]Under the small open economy with fixed world prices, a decrease in agricultural productivity induces resources to move toward manufacturing, which has become relatively more productive.

Donaldson (2012), Uy et al. (2013), and Caselli et al. (2012), who argue that reductions in trade barriers not only lead to lower fractions of the workforce employed in subsistence agriculture characterized by low productivity, but also lessen real income volatility.[8]

Another closely related study is the paper by Dell, Jones, and Olken (2012). The authors identify the effects of yearly fluctuations in temperature on economic growth, and show that the effects are stronger in poor countries. Using an empirical framework that involves long lags of temperature, the authors focus on testing the existence of the *level effect* (e.g.,"the effect of current temperature on crop yields") and the *growth effect* (e.g.,"the effect on features, such as institutions that influence productivity growth"). My paper complements their findings by providing evidence for the underlying mechanisms with the data analysis linking weather shocks, the price channel, factor reallocations, and output, which is in line with the proposed general equilibrium theory.

Many papers in the empirical development literature use rainfall shocks as a source of exogenous income shocks in developing countries (e.g., Miguel, Satyanath, and Sergenti, 2004; Jayachandran, 2006; Burgess and Donaldson, 2012; Burgess, Deschenes, Donaldson, and Greenstone, 2013). In those papers, implications of how rainfall shocks affect aggregate income are limited within agriculture, even though agriculture is only a part of the economies (the average share of agriculture in 2008 was 24% in low-income countries with per capita income less than $4,000). This paper contributes to this literature by suggesting a systematic mechanism in which rainfall shocks can affect not only agriculture but also other sectors through general equilibrium linkages.

This paper is also closely related to the literature on structural change and the role of agriculture in economic development (Gollin and Rogerson, 2014; Kevin Donovan, 2014; Herrendorf, Rogerson, and Valentinyi, 2013; Lagakos and Waugh, 2013; Restuccia, Yang, and Zhu, 2008; Gollin et al., 2002, 2007; Laitner, 2000; Matsuyama, 1991). Those papers focus primarily on the long-term growth path toward an industrialized economy (or growth of service sectors) beyond subsistence food production, or on explaining certain static economic characteristics of developing countries (such as low agricultural productivity and high agricultural employment shares, compared to developed countries).[9] My paper differs from the literature in that I focus on the differing impact of productivity shocks on short-run output fluctuations across poor and rich countries and econometrically estimate the channel using observable and exogenous shocks.

Like this paper, Colmer (2016) and Santangelo (2016) also investigate how shocks to agriculture affect manufacturing, but within districts in India. A distinct difference from

[8]David Atkin (2012), on the other hand, demonstrates that short-run gains from agricultural trade liberalization are limited because of household preferences that are biased toward locally abundant foods.

[9]Restuccia, Yang, and Zhu (2008) explain poor countries' large shares of employment in agriculture and low aggregate productivity using a two-sector model featuring Stone-Geary preferences. Matsuyama (1990) and Gollin et al. (2007) also use a two-sector model with the same type of preferences to study the central role of agricultural productivity in economic development. Kevin Donovan (2014) argues that, given uninsurable shocks, being close to the subsistence level causes poor countries to use less intermediate inputs, which amplifies differences in agricultural productivity between poor and rich countries.

my paper is that their analysis is done at the level of districts (within a country) which can be considered as small open economies, while this paper uses data on countries which are relatively closed to trade, especially in agriculture. Accordingly, Colmer (2016) finds that a reduction in agricultural productivity (caused by increases in temperature) causes workers to move into casual manufacturing activities, which is consistent with the prediction of the small open economy model in this paper. Santangelo (2016), on the other hand, focuses on locally traded goods. She finds that a negative productivity shock caused by rainfall shortages lowers local demand and reduces firm production and employment, which is consistent with the baseline model prediction in this paper. In sum, this paper provides macroeconomic evidence with varying degrees of the income effect depending on countrywide characteristics such as income levels, financial development, agricultural seasonality, trade openness, and so on, while those papers focus on microeconomic evidence within a single country.

Lastly, Da-Rocha and Restuccia (2006) also use a two-sector model in which one sector's productivity shocks affect the other sectors' output through general equilibrium linkages. They show that aggregate output volatility increases with the share of agriculture in the economy due to the increasing amount of intra-temporal substitution of consumption across sectors. However, the key mechanism is different in my paper, as it is primarily the income effect that causes fluctuations in output. While those authors use homothetic preferences, I use non-homothetic preferences, and in my model, income effects dominate substitution effects.

The remainder of the paper is organized as follows. Section 2 builds a two-sector general equilibrium model and describes the mechanisms through which agricultural productivity affects manufacturing output. Section 3 presents quantitative analysis to study the magnitudes of the effects across countries. Section 4 describes the econometric estimation strategy and data, and section 5 discusses the estimation results. Section 6 presents open economy models. Section 7 offers concluding remarks.

2 Two-Sector General Equilibrium Model

This section builds a static general-equilibrium model with two sectors: agriculture and manufacturing. Both sectors employ two factors, labor (L) and capital (K), which are assumed to be perfectly mobile within a country so that in equilibrium there will be one wage rate (w) and one capital rental rate (r) in a country. This section assumes a closed economy, which is partly justified by low agricultural trade volumes in the real world, where governments impose barriers to agricultural trade to protect domestic markets from international price variability (e.g., Anderson and Nelgen, 2012; Gouel, 2012).[10] There exists L mass of population, each endowed with one unit of labor and $\frac{K}{L}$ units of capital. In this section, I assume $L = 1$ for simplicity.

[10]Two other reasons are: (1) biased consumer preferences toward locally abundant foods (Atkin, 2012), (2) high transportation costs, since food is bulky and heavy (Tombe, 2015; Gollin and Rogerson, 2014; Caselli et al., 2012).

I assume a perfectly competitive economy with many small identical firms in each sector. The production technology of each sector is represented by the Cobb-Douglas production function:

$$Y_i = f_i(K_i, L_i) = z_i K_i^{\beta_i} L_i^{1-\beta_i}, \quad i = a, m, \tag{1}$$

where z_i denotes industry i specific total factor productivity (TFP), $K_a + K_m = K$, and $L_a + L_m = L$. Given the prices, each sector chooses K_i and L_i to maximize profits,

$$\pi_i = p_i f_i(K_i, L_i) - wL_i - rK_i.$$

In Appendix C, I present a model using a new agricultural production function that incorporates land and intermediate inputs, and show that the key implication of the model is unchanged.

On the demand side, a representative agent has a CES utility function with a subsistence requirement for agricultural goods γ_a (CES Stone-Geary preference),

$$U = [\alpha(q_a - \gamma_a)^{(\sigma-1)/\sigma} + (1-\alpha)q_m^{(\sigma-1)/\sigma}]^{\sigma/(\sigma-1)}, \quad 0 < \alpha < 1 \text{ and } \sigma > 0, \tag{2}$$

where α and $(1-\alpha)$ are utility weights over the two goods; σ is the elasticity of substitution. The agent earns income $I = wL + rK$ by inelastically supplying L units of labor and lending K units of capital. The budget constraint is given by $p_a q_a + q_m = I$, where p_a is the price of the agricultural good relative to manufacturing, and the manufacturing price is normalized to unity. Solving the utility maximization problem yields the following manufacturing expenditure equation:

$$E_m = \widehat{\alpha_m}(\sigma, p_a) \cdot (I - p_a\gamma_a), \tag{3}$$

where $\widehat{\alpha_m}(\sigma, p_a) = \frac{(1-\alpha)^\sigma}{\alpha^\sigma p_a^{1-\sigma} + (1-\alpha)^\sigma}$. $\widehat{\alpha_m}(\sigma, p_a)$ indicates the share of residual income spent on manufacturing, and $\widehat{\alpha_m}(\sigma, p_a) \to (1-\alpha)$, as $\sigma \to 1$. The representative agent first spends $p_a\gamma_a$ for γ_a units of the agricultural good, and then allocates the residual income $I - p_a\gamma_a$ to the two goods depending on the weights, $\widehat{\alpha_m}(\sigma, p_a)$ and $\widehat{\alpha_a}(\sigma, p_a)(= 1 - \widehat{\alpha_m}(\sigma, p_a))$.

Given the above setup, I first assume $\sigma = 1$ in the following subsection. The CES preference then becomes a simple Cobb-Douglas preference, which enables me to algebraically identify key mechanisms in the general equilibrium outcome. I then briefly explore the general case in subsection 2.2.

2.1 Baseline Model ($\sigma = 1$)

The CES Stone-Geary utility function converges to the following Cobb-Douglas Stone-Geary function as $\sigma \to 1$:

$$U = (q_a - \gamma_a)^\alpha q_m^{1-\alpha}, \qquad 0 < \alpha < 1. \tag{4}$$

Equation (3) shows that the weight $\widehat{\alpha_m}(\sigma = 1, p_a)$ becomes $(1-\alpha)$, which is constant and no longer depends on the agricultural price; thus $E_m = (1-\alpha) \cdot (I - p_a\gamma_a)$.

To uncover the key properties of Stone-Geary preferences, I examine the food price elasticity and income elasticity of expenditure on manufacturing, which are given by:

$$\eta_{p_a} = \frac{\partial E_m}{\partial p_a}\frac{p_a}{E_m} = -\frac{p_a\gamma_a}{I - p_a\gamma_a} \tag{5}$$

$$\eta_I = \frac{\partial E_m}{\partial I}\frac{I}{E_m} = \frac{I}{I - p_a\gamma_a} \tag{6}$$

First, note that the signs of the two elasticities are opposite. The expenditure on manufacturing decreases with the food price, while it increases with the level of income. In fact, (5) implies (6), as an increase in food prices means a decrease in the residual income $I - p_a\gamma_a$. In this expenditure system, the income is split into a subsistence income component $p_a\gamma_a$ and a residual income component $I - p_a\gamma_a$. With $\sigma = 1$, food prices affect the division of income into these components, but do not affect the share of residual income spent on manufacturing (which is simply the utility weight $1 - \alpha$). Second, the magnitudes of the two elasticities become arbitrarily large when I gets close to the subsistence level $p_a\gamma_a$. This implies that shocks to food prices or to income will translate into larger fluctuations of manufacturing demand in poor countries. This income effect is the key feature of the model that causes differing patterns of volatility in poor and rich countries. Lastly, as I tends to infinity, η_{p_a} and η_I approach zero and one, respectively, as the minimum expenditure requirement becomes negligible compared to the level of income.

Competitive equilibrium and the effect of a change in agricultural productivity on manufacturing — Next, I derive equilibrium solutions and study how changes in agricultural productivity affect equilibrium manufacturing output differently in poor and rich countries. The competitive equilibrium of the closed economy is a set of allocations $\{L_a, L_m, K_a, K_m, q_a, q_m\}$ and prices $\{w, r, p_a\}$, such that, given the prices, (1) $\{q_a, q_m\}$ solve the utility maximization problem of the representative agent, (2) $\{L_a, L_m, K_a, K_m\}$ solve the profit maximization problem of each sector, and (3) all markets clear. Each equilibrium allocation can then be expressed by the eight parameters, $K, L, z_a, z_m, \beta_a, \beta_M, \alpha$, and γ_a.

The model structure implies that changes in z_a can affect manufacturing output only through the reallocation of labor and capital resources. Thus, I study either the solution for L_m or K_m. Appendix A.1 shows that the implicit solution for L_m is given by:

$$\frac{1}{z_a}\cdot\frac{\gamma_a}{K^{\beta_a}} = G(L_m), \tag{7}$$

where $G(L_m) = \frac{L - \lambda^{-1}\cdot L_m}{[L + \frac{(\beta_m - \beta_a)}{\beta_a(1-\beta_m)}L_m]^{\beta_a}}$ and $\lambda = \frac{(1-\alpha)(1-\beta_m)}{(1-\alpha)(1-\beta_m)+\alpha(1-\beta_a)}$. Equation (7) is not a closed form solution, but it allows for convenient interpretation. We can verify that the value of function G decreases with L_m by taking the derivative of G. This implies that equilibrium labor allocation for manufacturing L_m increases with agricultural productivity z_a, leading to the positive link between agricultural productivity and manufacturing output. That is, a decrease in z_a pulls resources out of manufacturing and into agriculture in order to meet the subsistence requirement, reducing manufacturing output. Equation (7) also implies that

L_m decreases with $\frac{\gamma_a}{K^{\beta_A}}$, which is the subsistence requirement relative to per capita capital stock. In other words, the higher the subsistence requirement relative to income, the lower the manufacturing output. The same patterns hold true for K_m, as it is positively correlated with L_m (see Appendix A.1).

Having shown the directional impact of agricultural productivity on resource reallocations, I next recall the main question of this paper: Does industrial output fluctuate more in poor countries in response to changes in agricultural productivity? This is equivalent to asking whether the elasticity of manufacturing output with respect to agricultural productivity is higher in low-income countries. It has been seen that food price elasticity of manufacturing demand decreases with income levels. Similar patterns hold in the general equilibrium context. Equation (7) shows that the greater $\frac{\gamma_a}{K^{\beta_a}}$ (which can be viewed as a magnification effect) is, the larger is the fluctuation of L_m in response to changes in z_a. Put differently, the elasticity of labor (and capital) in manufacturing with respect to z_a decreases with income levels, which also implies that the elasticity of manufacturing output decreases with income levels. This is the key observation in this model, which leads to higher levels of industrial output volatility in poor countries. Another important implication is that resources are moving toward agriculture when agricultural productivity is declining. Such reallocation of resources can result in a large reduction in aggregate productivity (see Appendix B and compare with the open economy case). I summarize the key implications of the baseline model as follows:

Implication 1: Labor and capital move away from manufacturing and into agriculture in response to a decrease in agricultural productivity. This effect decreases with income levels.

Implication 2: The elasticity of manufacturing output with respect to agricultural productivity is positive and decreases with income levels.

Implication 3: A decrease in agricultural productivity can lead to a significant reduction in aggregate productivity as resources move toward the sector with declining productivity. This effect decreases with income levels.

The first two implications will remain as core theoretical predictions throughout this paper. Section 3.2 will show that calibration results of the original model generate the same implications, although $\sigma \neq 1$ may weaken or strengthen the effects. Hence, in the following subsection I investigate how σ interacts with the income effect, and derive generalized equilibrium solutions.

2.2 CES Stone-Geary Preferences ($\sigma \neq 1$)

In the baseline model, the distinct feature of the Cobb-Douglas Stone-Geary preference is that consumers spend constant shares (α and $1-\alpha$) of their residual income $I - p_a\gamma_a$ on food and manufactures, regardless of changes in prices. However, when $\sigma \neq 1$, Equation (3) indicates that the weight $\widehat{\alpha_m}(\sigma, p_a)$ depends on the agricultural price as well as sigma. Using Equation (3), I obtain the food price elasticity of manufacturing expenditure as follows:

$$\begin{aligned}\eta_{p_a,CES} = \frac{\partial E_m}{\partial p_a}\frac{p_a}{E_m} &= (\sigma-1)\frac{\alpha^\sigma p_a^{1-\sigma}}{\alpha^\sigma p_a^{1-\sigma}+(1-\alpha)^\sigma} - \frac{p_a\gamma_a}{I-p_a\gamma_a} \\ &= \underbrace{(\sigma-1)\widehat{\alpha_a}(\sigma,p_a)}_{\text{substitution effect}} + \underbrace{\eta_{p_a}}_{\text{income effect}} ,\end{aligned} \tag{8}$$

where η_{p_a} is the food price elasticity (which is a function of income) in the Cobb-Douglas case (see Equation (5)).

The first term (substitution effect) is negative when $\sigma < 1$, and it is positive when $\sigma > 1$. Meanwhile, the second term (income effect) is negative and clearly decreases with income levels. More specifically, when $\sigma < 1$ ($\sigma > 1$), a rise in the food price p_a generates the two effects: (1) the substitution effect raises (lowers) the share of residual income spent on food, and lowers (raises) the expenditure on manufacturing; (2) the income effect lowers the residual income, and lowers the expenditure on manufactures. Since p_a is inversely related to z_a, a decrease in z_a will decrease (increase) $\widehat{\alpha_m}(\sigma, p_a)$ and decrease $I - p_a\gamma_a$. In other words, $\sigma < 1$ increases the income effect, while $\sigma > 1$ abates the income effect. Note that as σ approaches 1 the substitution effect goes away and $\eta_{p_a,CES}$ approaches η_{p_a}. When I becomes arbitrarily large, the income effect disappears and only the substitution effect remains.

Finally, solving the model with the original setup (as described in the beginning of section 2) yields the following implicit solution for L_m (see Appendix A.2 for the derivation):

$$\frac{1}{z_a}\cdot\frac{\gamma_a}{K^{\beta_a}} = \tilde{G}(L_m), \tag{9}$$

where $\tilde{G}(L_m) = \frac{L-\lambda_2(p_a)^{-1}\cdot L_m}{[L+\frac{(\beta_m-\beta_a)}{\beta_a(1-\beta_m)}L_m]^{\beta_a}}$; $\lambda_2(p_a(L_m)) = \frac{\widehat{\alpha_m}(\sigma,p_a)(1-\beta_m)}{\widehat{\alpha_m}(\sigma,p_a)(1-\beta_m)+\widehat{\alpha_a}(\sigma,p_a)(1-\beta_a)}$; $p_a(L_m) = \frac{z_m\beta_m}{z_a\beta_a}[\frac{\beta_a(1-\beta_m)L+(\beta_m-\beta_a)L_m}{K}]^{\beta_a-\beta_m}[\beta_m(1-\beta_a)]^{\beta_m-1}[\beta_a(1-\beta_m)]^{1-\beta_a}$. This implicit solution looks similar to the solution of the baseline model (Equation (7)) except that the constant utility weight α of the Cobb-Douglas preference is now a function of p_a and σ. The next subsection will show that the baseline model simulation results are robust to using this CES model given relevant parameter values, since the income effect dominates the substitution effect.

3 Quantitative Analysis

This section complements the theory with numerical results, in order to see how much output change the model can generate across countries and investigate whether the magnitudes of the effects are significant and plausible. I calibrate the model using basic economic features across countries such as endowments, productivity, employment shares, and total output in agriculture and manufacturing. I then examine effects of agricultural productivity shocks on resource reallocations and manufacturing output by simulating the equilibrium solutions. The key questions in this section are: (1) How does a change in agricultural productivity affect resource reallocations differently depending on income levels? (2) How do such resource reallocations affect manufacturing output? (3) What are the quantitative predictions about output volatility? The first two subsections present results on the baseline model, followed by another subsection that discusses results with $\sigma \neq 1$.

3.1 Baseline Model Calibration

Recall that each equilibrium allocation $(L_a, L_m, K_a, K_m, q_a, q_m)$ is a function of the eight parameters, $K, L, z_a, z_m, \beta_a, \beta_M, \alpha$, and γ_a. The total amount of labor L is normalized to 1. Per capita capital stock K across countries is constructed based on the investment data of the Penn World Table 7.1 and is normalized by Ethiopia's.[11] Ethiopia is chosen to be a base country, as it is one of the poorest countries in UNIDO (2011) manufacturing data, and its per capita income is close to the lower poverty line ($275 in 1989 US dollars) proposed by the World Bank (1990).[12] The production function indexes β_m and β_a, which are capital income shares in each sector, are set to 0.58 and 0.32, respectively, according to the GTAP (2007) input-output table of India.[13] The capital income share in manufacturing/agriculture is calculated as the ratio of the value of capital stock to the sum of capital stock value and labor compensation value in the sector.

Next, we need a series of shocks to agricultural productivity $\{z_{a,t}\}_{t=1970}^{t=2002}$ for each country. Yield (production per hectare of land) is often used as a measure of productivity, but it also depends on inputs.[14] To justify the usage of yields for agricultural total factor productivity (TFP) in the model, I assume that each unit of land uses a fixed amount of input combination ($c = k_{a,t}^{\beta_a} l_{a,t}^{1-\beta_a}$, where c is constant), and the total area of land varies depending on the total amount of input combination in agriculture ($cZ_t = K_{a,t}^{\beta_a} L_{a,t}^{1-\beta_a}$, where Z_t is land). This way, $z_{a,t}$ is directly proportional to yield. Assuming this, the yearly values of $z_{a,t}$ for each country are set at each country's annual cereal yields (measured as kilograms per hectare of harvested land, including wheat, rice, maize, etc.; taken from the FAO) for the period 1970-2002 and are divided by Ethiopia's minimum cereal yield, which is 974kg/hectare. Although cereal production is only a part of agriculture, I assume that its productivity is highly associated with production of other plants and animals (animals are fed with cereals and plants). The average $z_{a,t}$ (during 1970-2002) for the U.S. is about 4.5, which implies that agricultural productivity in the U.S. is more than four times as high as Ethiopia's. Meanwhile, z_m is set to be a free parameter that matches each country's income earned from agriculture and manufacturing. z_m for Ethiopia is normalized to 1, and z_m for other countries are set at those values so that the income levels implied by the benchmark model are the same as the real per capita income data normalized by Ethiopia's.

[11] I assume initial capital stock in 1960 to be twice the total GDP and the annual capital depreciation rate to be 6%.

[12] Defining a proper base country is important in the model with preferences featuring a subsistent requirement in order to avoid corner solutions. All other parameter values are also assigned to ensure interior solutions for all countries.

[13] I choose India to obtain factor income shares because this paper focuses on developing countries. The country size is big enough, so the equilibrium economic outcome is less likely to be driven by some country-specific characteristics.

[14] Note that one cannot plug yield values for output in the model equation to obtain z_a, because output has to be an equilibrium outcome.

The Stone-Geary utility weight α can be interpreted as food expenditure share when the subsistence level relative to income is negligible. However, it is hard to define and obtain actual food expenditure data because, for example, food away from home includes service. Thus, I instead use employment data and Equation (7), which gives an equilibrium solution for employment in manufacturing, to calibrate both α and the subsistence requirement γ_a. The manufacturing employment share (out of total employment in agriculture and manufacturing) for the U.S. in year 2004 is 91%, while it is only 7% in Ethiopia.[15] I plug these numbers back into L_m in Equation (7), with country-specific K and z_a for the U.S. and Ethiopia, and obtain two equations with two unknown variables α and γ_a. Solving for α and γ_a yields $\alpha \approx 0.018$ and $\gamma_a \approx 0.891$.

Note that whether a country is poor or rich in the model is determined by the given values of capital stock K_c (c denotes a country), manufacturing productivity $z_{m,c}$, and an average value of agricultural productivity $z_{a,c}$. With these, the two-sector model with Stone-Geary preferences can generate the fact that the expenditure share for the subsistence requirement tends to decrease with income levels. For example, it is 89% in Ethiopia, while it is only 4% in the U.S. (see column 3 of Table 2). To summarize, Table 1 presents the assigned parameter values and the data source.

3.2 Quantitative Results (Baseline Model)

Given the calibrated parameters, this section presents simulation results of the baseline model. First, I study how a 15% agricultural productivity shock affects manufacturing output.[16] Second, I consider a series of shocks, given by the cross-country time-series data on crop yields. I then calculate volatilities of simulated manufacturing output.

In the model, levels of total capital stock and productivity determine the level of economic development. As can be seen from the first two columns of Table 2, a country's capital stock and average value of agricultural productivity (denoted as $z_{a,c}$, where c is a country) are roughly increasing with the country's income level. Based on those values and other calibrated parameters, column 3 reports numerical results on the shares of subsistence requirement out of total income ($\frac{p_a \gamma_a}{I}$) across countries. Since a poor country spends a high portion of its income for the subsistence food requirement, on the production side a large share of labor and capital resources has to be devoted to agriculture (see column 4 of Table 2, where $L_a^* = 1 - L_m^*$).

A 15% productivity shock — We now consider a 15% decline in agricultural productivity. Equilibrium agricultural prices rise in all countries by about 20% (column 5 of Table 2). Due to the increases in agricultural prices, labor and capital resources move toward agriculture for

[15] Admittedly, more than 80% of the total employment works in service sectors in the U.S. However, the model assumes only agriculture and manufacturing, and a decline in agricultural productivity is pulling factors only out of manufacturing (not services). One way to solve this problem is to treat manufacturing and services as an aggregate.

[16] Note that the average value of annual percentage change in crop yield was 14.7% across countries in the sample.

higher profits, leading to reductions in employment and capital in manufacturing (columns 6 and 7). As a result, manufacturing output decreases in all countries, and the magnitude of output change decreases with income levels due to decreasing income effects (column 8 of Table 2). An important point is that the baseline model is able to generate significant differences in magnitudes across countries. For example, manufacturing output decreases by 17% in Ghana, whereas it decreases only by 0.6% in the U.S.[17]

Table 2 shows that some resources will be reallocated toward the sector with declining productivity. How would this affect aggregate productivity? In Appendix B, I decompose the changes in aggregate TFP into the productivity effect (within-sector effect) and the share effect (between-sector effect). I show that the share effect is negative due to the movement of resources toward agriculture with declining productivity. For example, in Ethiopia, the share effect is -2.2% out of a -13.5% change in aggregate TFP, and the effect becomes negligible in rich countries (see Table A.6). In contrast, if one assumes an open economy which allows resources to move into the sector with increasing productivity the share effect can become positive, which substantially lessens the reduction of aggregate TFP (from -13.5% to -7.6% in Ethiopia, for example).

Volatility: a series of shocks to yields — I turn to measuring volatility of manufacturing output, using the cross-country time-series data on crop yields as a series of agricultural productivity shocks. In the baseline model, the manufacturing output volatility of a country can be large when the size of shocks is large and when the country's income is close to the subsistence level. First, I measure the size of shocks by calculating the standard deviation of growth rates in crop yield, which I call crop yield volatility (column 1 of Table 3). Among the selected countries in Table 3, Malawi exhibits the highest yield volatility at 45.8%, while Bangladesh exhibits the lowest at 5.6%.

Given the country-specific shocks, we can calculate manufacturing output volatility based on the simulation results of the baseline model. Consistent with the theory, poor countries tend to exhibit higher levels of manufacturing output volatility (column 2 of Table 3). Admittedly, for some poor African countries, the magnitudes of simulated volatilities are larger than the volatilities directly calculated from the data (see columns 2-3). One reason for this might be the closed economy assumption in the baseline model. In section 6, I show how the magnitudes can be attenuated in open economy models. Lastly, note that countries that are subject to large shocks exhibit higher manufacturing output volatility. For example, even though Portugal is much richer than Bangladesh, Portugal's implied volatility is slightly higher, mainly because crop yield volatility is three times higher in Portugal.[18]

[17]The result shows that output decreases by more than 50% in Ethiopia. This is mainly because Ethiopia serves as a base country whose income is set to be right above the subsistence level. As shown in equations (5) and (6), the effect can be very large when the income is close to the subsistence level.

[18]It is also partially due to the lower agricultural productivity in Portugal; as shown in Table 2, the average yield in Portugal is 1.77 while it is 2.36 in Bangladesh.

3.3 Quantitative Results (CES Stone-Geary Preferences)

In this subsection, I re-simulate the general equilibrium solutions of the CES model (see Equation (9)) with varying σ and compare them with the baseline model results. Herrendorf, Rogerson, and Valentinyi (2013) estimate the elasticity of substitution in consumption across agriculture, manufacturing, and service sectors to be 0.85. Meanwhile, Da-Rocha and Restuccia's (2006) estimated elasticity of substitution between agriculture and non-agriculture is 0.52 in a model with a homothetic preference. However, I presume that it is also possible for σ to be larger than 1 when it comes to the preference regarding agriculture and manufacturing with a subsistence requirement. Accordingly, I set $\sigma = 0.52, 0.85, 2.5$, and for all other parameters I use the same values as listed in Table 1 for comparison with the baseline model results.

Columns 2 and 3 of Table 4 show that, for $\sigma = 0.52, 0.85 < 1$, manufacturing output decreases only slightly more compared to the baseline model case, in response to a 15% decrease in z_a. In Ghana, manufacturing output declines by 17.235% in the baseline model, while it decreases by 17.32% (18.441%) when $\sigma = 0.85$ ($\sigma = 0.52$) in the CES model. Note that the total effect on manufacturing output equals the sum of the income effect (causing a positive link between z_a and q_m) and the substitution effect (also causing a positive link when $\sigma < 1$). This implies that the substitution effect resulted in only about 0.1% decrease in manufacturing output in response to the increase in food prices.

When $\sigma = 2.5 > 1$, on the other hand, manufacturing output decreases slightly less compared to the baseline model case (column 4 of Table 4). With $\sigma = 2.5$, substitution effect resulted in an increase of about 0.001% in manufacturing output in response to the increase in food prices. Note that due to the small utility weight attached to agricultural products ($\alpha \approx 0.018$), the substitution effect caused by agricultural shocks is also small. I show in Appendix A.2 that interesting volatility patterns can be generated when α becomes 0.5.

In sum, the baseline model simulation results are close to the results using CES preferences with parameters in appropriate ranges, as the income effect dominates the substitution effect.

4 Econometric Estimation

4.1 Empirical Strategy: Instrumental Variable Approach

The baseline model suggests that a decrease in agricultural productivity shifts resources away from manufacturing and into agriculture, thus reducing manufacturing output (positive link between agricultural productivity and manufacturing output). This effect decreases with income level. To test these predictions, we need exogenous movements in agricultural productivity which vary across countries and time. I use crop yields as a proxy for agricultural productivity, and capture exogenous variation in yields using rainfall shocks.

Main estimating equation — The unit of observation is a country c in a given year t, and the main estimating equation is,

$$\Delta q^m_{c,t} = \alpha_c + \alpha_t + \beta_0 + \beta_1 \cdot \Delta yield_{c,t} + \beta_2 \cdot \Delta yield_{c,t-1} + \epsilon_{c,t} \ , \tag{10}$$

where $\Delta q^m_{c,t} = ln\frac{q^m_{c,t}}{q^m_{c,t-1}}$; $q^m_{c,t}$ and $yield_{ct}$ denote manufacturing output and crop yield in country c in year t; α_c is a country fixed effect that captures country-specific time trends of manufacturing output such as technological progress; α_t is a time-fixed effect; and $\epsilon_{c,t}$ is an idiosyncratic error term.

Using the simple framework, I test whether the coefficient β_1 or β_2 is significantly positive and whether the effect is larger in less-developed economies. Note that including income levels interacted with yield growth is avoided due to multicollinearity with other important variables such as the share of agriculture, the level of financial development, and openness to trade. These variables are highly correlated with each other, as there are only 118 countries in the dataset. Hence, I instead run separate regressions on different groups of countries depending on income levels and the other variables.

Estimating the model in first-differences simplifies the framework by eliminating country specific and short-run time invariant effects (e.g., gradual changes in sector specific technology, climate conditions due to global warming, or industrial composition of the country). Note that this estimation framework resembles the calibration exercise shown in Table 2, which examined manufacturing output growth rates across countries in response to a decrease in agricultural productivity. The above equation also includes lagged yield growth in order to allow for a time lag between an agricultural shock and its impact on manufacturing – for example, in the northern-hemisphere where the harvest occurs in the fall, the effect of the shock on manufacturing may exist in the following year data. Similarly, agricultural seasonality can affect estimation results significantly. I address this issue by grouping countries depending on the latitude, and show that consideration of seasonality is indeed very important for the results.

For robustness checks, I use other variables to ensure that the estimation results are driven by the theoretical mechanisms. Note that the theory also predicts that higher openness to trade weakens income effects (see section 6) and that larger shares of agricultural production out of total GDP strengthen the model prediction. I examine these using data on international trade and agricultural output. Meanwhile, recall that this paper introduced relatively simple models that do not incorporate some features that may be important to other studies. For example, if a country has a well-developed financial system, the effect of agricultural shocks on resource reallocations may decline because each sector can hedge against economic shocks by savings and borrowings. Hence, I additionally test how the level of financial development affects the extent to which agricultural shocks impact manufacturing output.

Importantly, input-output linkages can be a concern for testing the proposed theory in aggregate level analysis. To avoid the direct impact of agricultural shocks on manufacturing, I exclude manufacturing sectors that use agricultural products as primary inputs (such as food, tobacco, or cotton). Admittedly, such effects still remain, which can be quantified using a simple model from Jones (2011) and OECD input-out data across countries.[19] I find that the direct input-output linkage effect induces a 10% increase in agricultural productivity to generate about a 0.3% increase in manufacturing output excluding food, tobacco, and textile-related sectors, in less developed countries with per capita GDP less than $10,000 (in 2005 international dollars). When all manufacturing sectors are combined, the effect substantially increases to 1.4%, which shows that excluding such sectors controls for the input-output linkage effect reasonably well. I will leave further analysis of the 0.3% increase as future work for the following reasons. One, estimation results in section 5.3 will show that the 0.3% input-output linkage effect is less than one-tenth of the estimate effect. Two, input-output data differ greatly across countries and even within developing countries, but the data are available only for a subset of developing countries.

Channels — The theory suggests the two-step channels through which agricultural productivity affects manufacturing output: productivity shocks affect food prices, and then some labor and capital resources reallocate between the two sectors. Using crop price data and manufacturing data on employment and capital investment, I test the channels using similar frameworks:

$$\Delta CropPrice_{c,t} = \alpha_c + \alpha_t + \beta_0 + \beta_1 \cdot \Delta yield_{c,t} + \beta_2 \cdot \Delta yield_{c,t-1} + \epsilon_{c,t} \ , \tag{11}$$

$$\Delta L^m_{c,t} = \alpha_c + \alpha_t + \beta_0 + \beta_1 \cdot \Delta yield_{c,t} + \beta_2 \cdot \Delta yield_{c,t-1} + \epsilon_{c,t} \ , \tag{12}$$

$$\Delta K^m_{c,t} = \alpha_c + \alpha_t + \beta_0 + \beta_1 \cdot \Delta yield_{c,t} + \beta_2 \cdot \Delta yield_{c,t-1} + \epsilon_{c,t} \ . \tag{13}$$

These specifications are also tested on different groups of countries with varying income levels, latitudes, openness to trade, shares of agriculture, and credit constraints.

Endogeneity and first-stage estimation — An important concern in estimating Equation (10) is that factors outside the model may affect both yields and industrial output, leading to a biased estimate effect. Consider two examples. First, suppose there is common technological progress that raises productivity in all sectors of the economy. This will generate positive correlation between yields and industrial output independent of the theoretical mechanism, leading to an upward bias in OLS results. Second, yields (output per unit of land) are used as a measure of agricultural productivity because they are consistently available for many countries and time periods. However, yields differ from the pure TFP measure, because they also depend on inputs. Since agriculture and manufacturing compete for the limited amount of resources in the economy, changes in policies that favor one sector over another will induce negative correlation between yields and manufacturing output. For example, when a government decides to subsidize agriculture, this may pull resources out of manufacturing and into agriculture, reducing manufacturing output and raising crop yields at the same time. This will cause a downward bias in the OLS results.

The solution for this issue is to find the source of exogenous variation in agricultural

[19] Using the model from Jones (2011), it can be shown $log(\Delta y) = (I - B')^{-1} log(\Delta Z)$, where Δy is a vector of real output changes in each sector; $(I - B')^{-1}$ is the Leontief inverse matrix; ΔZ is a vector of TFP changes across sectors (only agricultural productivity changes from 1 to 1.1).

TFP. Detailed studies of agricultural production show that yields are sensitive to changes in rainfall and temperature (e.g., Lobell et al., 2007; Schlenker et al., 2009). I use only rainfall shocks, as some studies show that heat can affect manufacturing workers' productivity and institutions that influence productivity growth, especially in poor countries (Dell et al., 2012; Jones and Olken, 2010; Colmer, 2016; Chen, 2003).[20]

In order to ensure that rainfall affects manufacturing output by affecting yields and not through other channels, I perform several robustness checks. First, I find that the labor movement effect in response to agricultural productivity is stronger and highly significant in countries with agricultural seasonality. Plus, I find that labor productivity in manufacturing hardly changes in response to rainfall. Second, results using rainfall applied to non-crop areas exhibit weaker effects (note that non-crop area rainfall is still correlated with crop-area rainfall, although the effect on yield is weaker). These results greatly weaken the possible operation of other non-agricultural channels.

The first-stage relationship between yield and rainfall is as follows:

$$\Delta yield_{c,t} = \eta_c + \eta_t + \gamma_0 + \gamma_1 \cdot \Delta rain_{c,t} + \gamma_2 \cdot \Delta rain_{c,t-1} + X_{c,t} + u_{c,t} \ , \tag{14}$$

where $X_{c,t} = tropic \cdot \Delta rain_{c,t} + tropic \cdot \Delta rain_{c,t-1}$; $\Delta rain_{c,t} = ln \frac{rain_{c,t}}{rain_{c,t-1}}$; η_c and η_t are country and year fixed effects, respectively; and $u_{c,t}$ is an idiosyncratic error term. I include interaction terms with a tropical region dummy, which is equal to 1 if the country has a tropical climate, since the rainfall effect on yield can be much smaller in such climate. Lastly, I include both rainfall growth rates at time t and $t-1$ to instrument for the two endogenous regressors, $\Delta yield_{c,t}$ and $\Delta yield_{c,t-1}$, in the main estimating equation (10).

4.2 Data

Manufacturing Data — Manufacturing data on annual output in value added, the number of employees, and gross fixed capital formation come from the 2011 UNIDO Industrial Statistics Database. I use the INDSTAT2 version, which reports the data according to the two-digit ISIC Revision 3 classification, for the period 1970-2002.[21] Although the original UNIDO dataset contains 23 sectors, I aggregate the sectors into 8 categories for two reasons. First, many countries (especially, low-income countries) report values that are aggregated from multiple sectors (for example, some countries combine metals and machinery together and report the data as metals). Second, sectors with similar characteristics are grouped into the same category to study sector-specific effects of agricultural productivity on manufacturing. The list of sectors is displayed in the Appendix Table A.2. Sector 1 (food and

[20] Jayachandran (2006) also uses crop yield as a proxy for agricultural TFP and rainfall shocks to instrument crop yields in order to study changes in agricultural wages in response to productivity shocks. Miguel et al. (2004) uses rainfall growth to instrument income growth in African countries and study the effect of economic conditions on the likelihood of civil conflicts. Dercon (2004) uses panel data from rural Ethiopia and rainfall shocks in order to study consumption growth.

[21] The results are also robust to using longer time-series 1961-2008 (see Appendix Tables A.7-10). Estimating 50 years of time series data across countries might be too extensive due to the rapidly changing world economic situation. Also, it is reasonable to consider the period before the onset of the unprecedented food crisis in 2007-8.

tobacco) and sector 2 (textile related industries that use cotton intensively) are excluded in aggregate-level regressions to avoid the direct impact of agricultural productivity on manufacturing output through agricultural inputs. After dropping countries with fewer than 5 consecutive year observations (in the number of employees, as this has fewer missing values than output and investment) and combining these data with other data, I have 118 countries in the analysis.

The first three rows in Table 5 show some statistics on the aggregated manufacturing data excluding the two sectors. For each country, I first calculate mean and standard deviations of yearly growth rates in manufacturing output, employment, and capital investment. I then report mean values of the calculated cross-country values in different income groups. First, it can be seen that output, employment, and capital investment grew about 6%, 3%, and 25% annually on average during the period 1970-2002 (see column 1 in Table 5). Second, volatilities are about twice higher for employment and output in poor countries (mean GDP per capita less than $4,000), compared to higher-income countries (mean GDP per capita greater than $10,000).

Precipitation Data — Precipitation data come from the *CRU-TS v3.10.01 (1901-2009) Monthly Historic Climate Database* released by the University of East Anglia. The dataset reports worldwide monthly precipitation at 0.5×0.5 degree resolution (approximately 56km×56km at the equator). The crop distribution data is taken from *Agricultural Lands in 2000, Ramankutty et al. (2008).* This dataset contains the distribution of global agricultural lands in the year 2000 at 5-minute resolution in latitude by longitude (approximately 7km × 7km at the equator). I aggregate these data to match the precipitation data at 0.5 × 0.5 degree resolution. In this dataset, each data point is assigned to a value ranging from zero to one, where the value is zero if there are no crops growing in the area and is one if the area is full of crops. Next, I construct another data layer that contains relative areas of all the grid cells on the globe using triple integrals in spherical coordinates, with the grid cell areas at the equator (approximately 56km×56km) equal to 1. Note that grid cell areas are smaller at higher latitudes. Lastly, another data layer that contains the world country border information is taken from the Thematic Mapping world borders dataset. This does not include small countries that do not fully contain any single grid cell (0.5×0.5 degree resolution), so all such small countries are naturally dropped from the analysis.

With these datasets, I use the GIS software to construct three types of annual rainfall data: crop-area weighted rainfall, non-crop area rainfall, and area weighted rainfall. First, crop-area weighted rainfall is the precipitation level weighted by crop density multiplied by the area of each grid cell within the country. That is, $CropRain_{c,t} = \sum_{i \in c} Rain_{i,c,t} \cdot \frac{C_{i,c}A_{i,c}}{\sum_{i \in c} C_{i,c}A_{i,c}}$, where $Rain_{i,c,t}$ is the sum of raw precipitation levels in the grid cell i in country c over 12 months in year t; $C_{i,c}$ is the crop density in the grid cell i in country c; $A_{i,c}$ is the area of a grid cell i in country c. This captures the amount of rainfall that is relevant to agricultural lands in each country (for example, in the Amazon precipitation levels are high, although no crops are growing in the region). Second, non-crop area rainfall is constructed by aggregating the precipitation data over the grid cells where the crop density is less than 10%, weighted again by grid cell areas in a country. That is, $NonCropRain_{c,t} = \sum_{i \in c} Rain_{i,c,t} \cdot \frac{I_{i,c} A_{i,c}}{\sum_{i \in c} I_{i,c} A_{i,c}}$, where $I_{i,c}$ indicates one if the crop density $C_{i,c}$ is less than 10% and zero otherwise. Third, I construct area weighted rainfall data by simply weighting precipitation by the grid cell area, $AR_{c,t} = \sum_{i \in c} Rain_{i,c,t} \cdot \frac{A_{i,c}}{\sum_{i \in c} A_{i,c}}$. I mainly use the crop-area weighted rainfall as instrument, and the other two are used for robustness checks.

Agricultural and other Economic Data — Cereal yield, the weight (kilograms) of crops produced per unit (hectare) of harvested land, is used as a measure of agricultural productivity. The data comes from the FAOSTAT and includes major staple crops such as wheat, rice, maize, barley, oats, rye, and millet. Crop price data on wheat, maize, rice, soybean, barley, and sorghum are also taken from the FAOSTAT. I use annual producer prices for the 1991-2008 period, which are provided by farmers through annual questionnaires. Since consumer prices are available only from the year 2000, I use producer prices instead, assuming that producer prices directly affect consumer prices.

Row 4 in Table 5 shows cross-country average values of within-country mean and volatilities of rainfall growth rates (crop-area weighted). It can be seen that the level of rainfall volatility, which corresponds to the size of exogenous productivity shocks from a particular source, is similar in poor and rich countries at about 23%. On the other hand, volatility of yield (see row 5) is significantly higher in poor countries (GDP per capita less than \$4,000) at about 26%, compared to the 16% yield volatility in higher-income countries (GDP per capita greater than \$10,000). One plausible explanation is that yield response to rainfall shocks is higher in poor countries (this is first-stage result, which will be shown in the following subsection) due to poor irrigation systems. There can be many other reasons other than rainfall, such as higher sensitivity to temperature and larger shocks to intermediate inputs in developing countries. Accordingly, rows 6-8 of Table 5 show that the crop prices tend to be highly volatile in poor countries.

Next, as a measure for openness to trade, I construct values of export shares in manufacturing output (aggregated over the sectors that do not use agricultural products as primary inputs) across countries, using the trade data from COMTRADE . The following two datasets are taken from the World Bank database: the share of agricultural value added as a share of GDP, and aggregate private credit provided by banks and other financial institutions as a share of GDP. Consistent with Levine et al. (2000), the private credit data is used as a measure of financial development. The two datasets are used to see whether the strength of theoretical predictions varies depending on those conditions. Lastly, PPP converted GDP per capita at 2005 constant prices and exchange rates to USD are taken from the Penn World Table 7.1.

5 Estimation Results

5.1 Crop Yield and Rainfall (first-stage results)

Table 6 presents the first-stage relationship between crop yield and the crop-area-weighted rainfall. I find that an increase in current year rainfall tends to raise yields of the same year in less developed countries, with t-statistics larger than 7 for all specifications. For example, a 10% increase in rainfall leads to a 2.8% increase in yield in countries with per capita GDP less than $10,000 (column 3). To consider the differing effects of rainfall in tropical and non-tropical climates, I include a tropical region dummy (which takes 1 if the country has a tropical climate and zero otherwise) interacted with the rainfall growth. I find that a tropical climate reduces the positive effect of rainfall on yield by more than 70% in all specifications that contain a reasonable number of tropical climate countries (columns 2 - 5), and the results are highly significant.

When I restrict the sample with per capita income below $4,000, the positive relationship between current year rainfall and yield become even stronger: a 10% increase in rainfall leads to a 3.4% increase in yield (column 2 of Table 6). The effect further increases to 4.2% in Sub-Saharan African countries (column 1). On the other hand, in higher income countries with per capita income greater than $10,000, the effect decreases by more than 70% (column 6). This implies that the effect of rainfall on yields tends to decrease with the level of economic development, which might be attributable to better irrigation systems in developed countries. Finally, note that the first-stage F-statistics in columns 1-5 are all greater than 20, implying that the crop-area-weighted rainfall is a strong instrument for yields in less developed countries.

5.2 Main Estimation Results

Agricultural productivity and manufacturing output — The theory implies that the income effect causes the positive relationship between agricultural productivity and manufacturing output, which is stronger when income levels are close to the subsistence level. Accordingly, Table 7 explores the second-stage relationship between yields (in log growth rates) and aggregate manufacturing output (in log growth rates; the aggregate output excludes the sectors that use agricultural products as primary inputs). I re-estimate the first stage for each specification across different dimensions, and report new F-statistics. Column 1 of Table 7 reports the OLS result for countries with per capita income less than $10,000 (in 2005 international dollars). The estimate of the lagged yield growth coefficient, which is the elasticity of manufacturing output with respect to yield, is 0.08. Meanwhile, the IV estimate (column 2 of Table 7) for the same coefficient is 0.19. Both results indicate the positive link between agricultural productivity and manufacturing output, which is consistent with Implication 2. However, the magnitude of the OLS result is much smaller than the magnitude of the IV result. As discussed in section 4.1, the fact that manufacturing and agriculture compete for the limited amount of resources in a country can result in a negative correlation between yield and manufacturing output. This makes yields endogenous, leading to the downward bias of the OLS result.

An important thing to note about the Table 7 results is that only the coefficients of lagged yield growth are significantly positive, while the current yield growth registers insignificantly. As mentioned in section 4.1, a plausible reason for this may relate to agricultural seasonality – especially for countries in the northern hemisphere – and a time lag between an agricultural shock and its impact on manufacturing. Indeed, column 5 shows that the lagged yield coefficient becomes more significant and larger when the sample is restricted to the northern hemisphere countries with minimum latitude at 20 degrees, which implies that a 10% decrease in yield leads to a 2.6% decrease in manufacturing output. On the other hand, the result is not significant for the sample countries near the equator (with latitudes between -20 and 20 degrees). This is in line with the theory, as agricultural workers have low incentive to move to and from manufacturing if the harvest occurs all year round. The relevant results on employment are shown in the next subsection.

The core theoretical prediction of this paper is that the income effect is stronger when the income level is close to the subsistence level. So far, I have shown that the estimation results are consistent with the theory for countries with per capita income less than $10,000. When I further restrict the sample to countries with per capita income less than $4,000, the lagged yield growth coefficient increases to 0.24 (column 8 of Table 7) from 0.18 (column 3) and is statistically significant. On the other hand, consistent with the theory, column 9 shows that the estimate becomes insignificant for higher-income countries (per capita income greater than $10,000).

I next examine how other variables such as the share of financial development, openness to trade, and agricultural GDP shares affect the strength of the model's predictions (Table 8).[22] First, I find that credit constraints have a strong impact on the result. Because the model assumes no saving and borrowing, the only way to compensate for an adverse shock to agriculture – in the presence of subsistence requirements – is to move resources away from manufacturing and into agriculture. Thus, if one can show that the effect of agricultural productivity on manufacturing is larger in countries with poor credit systems, the key argument of the theory is strengthened. Indeed, when the sample is further restricted by private credit less than 30% of GDP – this is quite low considering that 80% is the average level for developing countries – the IV result on the lagged yield growth jumps to 0.29 from 0.18 with 1% statistical significance (column 2 of Table 8, compared with the column 1 baseline result). Note that the average per capita GDP of this sample with poor credit system is $4,287 (column 2 of Table 8), which is much higher than $2,063, the average income of the sample with the $4,000 maximum income cutoff (column 8 of Table 7). Even if the average income is higher, the estimated elasticity, 0.29 shown in column 2 of Table 8 is greater than

[22]A better way to test this might be to include those variables interacted with yield growth in the estimating equation. However, they are highly correlated with one another, along with per capita income levels, and they all significantly affect the extent to which agricultural shocks impact manufacturing. Given that the number of countries in the sample is only 118 with fewer than 2000 observations in total, including all those relevant measures in the estimation leads to multicollinearity.

the elasticity, 0.24, shown in column 8 of Table 7. This implies that the fluctuations of output in response to agricultural productivity shocks can be higher despite the higher income levels, if the countries suffer from poor financial systems.

Second, an important implication associated with the open economy model (see section 6) is that the strength of the positive link will decrease with the trade openness. To investigate this, I restrict the sample to countries with low trade openness (the export share in manufacturing output less than 20%), and I find that the lagged yield growth coefficient becomes even larger, 0.31 (column 3 of Table 8). In contrast, the positive link becomes insignificant when the countries are relatively more open to trade (export shares greater than 20%; this result is not shown). Both results strongly support the theoretical prediction. Third, the theory implies that the role of agricultural productivity will be stronger when the share of agriculture is large. Consistently, column 4 of Table 8 points to a larger estimate of the lagged yield growth coefficient when the sample is further restricted by agricultural production shares greater than 10% of total GDP (compared with the column 1 baseline result).

For further robustness checks, I construct non-crop area rainfall data by aggregating the precipitation data over the grid cells where the crop density is less than 10%. I then use this as an instrument with the same first-stage specification as before. Columns 5-7 of Table 8 show that the second-stage results using the non-crop area rainfall become less significant, even if non-crop area rainfall tends to be highly correlated with crop-area rainfall within a country. This weakens the possibility of other channels than the one proposed by this paper.

Predicted industrial output volatility — Finally, I investigate the contributions of rainfall shocks to yields on industrial output fluctuations. Table A.3 reports standard deviations of predicted manufacturing output growth rates obtained from the following IV estimation result for the Northern-hemisphere countries with average per capita GDP less than \$10,000:

$$\widehat{\Delta q^m_{c,t}} = \widehat{\alpha}_c + \widehat{\beta}_0 + \widehat{\beta}_1 \cdot \Delta \widehat{yield_{c,t-1}}.$$

This specification is almost the same as the regression (3) in Table 7 except that this does not include current-year yield growth (as the estimate is not significant) and the exchange rate (as I want to calculate volatility caused only by yield fluctuations).

Using the above equation, I present two types of predicted volatility. First, I report standard deviations of $\widehat{\Delta q^m_{c,t}}$ when the projections of rainfall onto yields are used for $\Delta \widehat{yield_{c,t-1}}$ (column 1 of Table A.3). The average value of such volatilities for the 38 sample countries is about 5.4%. Second, column 2 of Table A.3 displays volatilities when the endogenous variable, the yield data, is directly used instead of $\Delta \widehat{yield_{c,t-1}}$, and the average volatility is about 7.1%. The manufacturing output volatilities calculated directly from the UNIDO data are also presented in column 3, where the average value is about 22.8%.

Next, I divide the two predicted volatilities by the real volatility, obtaining average values of 0.31 and 0.44, respectively (see columns 4-5 of Table A.3). This implies that the crop yield variations induced by rainfall shocks can explain about 31% of manufacturing output fluctuations in developing countries. Note that there are other important factors that affect agricultural production, such as temperature and access to intermediate inputs. With the strong assumption that all the variations in the yield data are not correlated with shocks to manufacturing, about 44% of manufacturing output volatility on average can be explained by the yield variations in the developing countries.

5.3 Evidence of Labor and Capital Reallocations

Importantly, the theoretical model suggests that agricultural productivity affects manufacturing output through the resource reallocation channel. When there is a negative shock to agricultural productivity, a drought for example, labor and capital resources move toward agriculture and out of manufacturing in response to an increase in food prices. This subsection presents strong evidence for the mechanism, which is in line with the main estimation results discussed above. I investigate changes in manufacturing employment and capital investment in response to exogenous shocks to agricultural productivity.

Labor movement between sectors — The labor reallocation channel is highly important in this analysis, as developing countries are labor abundant and most industries are labor intensive. Hence, worker movement between the sectors can have a substantial impact on output. To test the labor reallocation effect, agricultural seasonality needs to be taken into consideration because labor movement is limited by many factors such as time, space, and willingness to migrate. To illustrate, an agricultural worker in a northern-hemisphere country has a higher incentive to move to other sectors after the harvest in the fall, because there is not much work to do during the winter and probably until the next harvest season.[23]

Table 9 reports estimation results of Equation (12). For the specifications that are in line with the theory (columns 2-5 and 7-8), all the estimated coefficients on the current year yield growth are highly significant at the 1% level, with the relatively consistent range of the magnitudes between 0.22 and 0.35. The OLS and IV estimates shown in columns 1 and 2 of Table 9 are 0.04 and 0.22, respectively, for the less developed countries in the Northern Hemisphere (income less than $10,000, with the 10-degrees minimum latitude cutoff). This pattern, the much smaller OLS estimate than the IV one, was observed in the previous results associated with output in Table 7. The competition for limited resources between manufacturing and agriculture may have caused the downward bias of the OLS result. Put differently, higher employment in manufacturing can be linked to lower yield due to lower labor input, which causes a negative correlation between the two variables.

The IV result in column 5 of Table 9 implies that a 10% decrease in current year yield leads to a 2.5% decrease in manufacturing employment in the same year, for the less developed countries (per capita income less than $10,000) located above 20-degrees latitude.

[23] Postel-Vinay (1994) discusses mobile temporary workers in eighteenth century France as follows: "...every summer thousands of industrial workers left their jobs to work in the grain fields. ... wheat production expanded most in districts where industrial workers were temporarily available for harvest work." Given the existence of mobile temporary workers in the eighteenth century, it might be reasonable to expect a similar situation in developing countries today.

When the minimum latitude cut is lowered to 10 degrees in the Northern Hemisphere, the effect slightly decreases to 2.2% (column 2 of Table 9). Moreover, for countries that are located closer to the equator (between -20 and 20 degree latitudes), the results become insignificant (column 6 of Table 9), which is consistent with the previous results on output. A plausible reason is that agricultural workers in this region may have low incentive to move to other sectors as the harvest takes place all year round.[24] These results associated with agricultural seasonality strongly support the key mechanism of the theory that a decrease in agricultural productivity reallocates labor out of manufacturing into agriculture to meet the subsistence requirement.

In addition, I find two interesting results associated with credit constraints and strong income effects. First, column 4 of Table 9 shows that when the sample is restricted to countries with relatively underdeveloped credit systems (private credit less than 30% of GDP), the elasticity increases by more than 30%, from 0.22 to 0.29, with a significantly increased t-statistic from 3.5 to 5.5 (compared with the baseline result in column 2 of Table 9). This result is consistent with the implication of the theoretical mechanisms as well as the previous estimation result for output with the same credit constraint (column 2 of Table 8). When borrowing/lending is not available, pulling workers out of manufacturing and into agriculture can help meet the subsistence requirement under a drought. Second, when the maximum income cutoff is lowered to $4,000, the labor reallocation effect for the northern hemisphere countries increases by more than 30% (columns 7-8 of Table 9). A plausible explanation for this phenomenon is that workers are more willing to move across sectors to find a job when their income levels are near the subsistence level. On the other hand, this effect disappears for countries with a per capita income greater than $10,000. These results are consistent with the main theoretical implication that the role of agriculture in resource reallocation diminishes with income levels.

Note that unlike the previous results associated with output shown in Tables 7-8, it is the coefficient on the current year yield growth that is significantly positive, while the coefficient for the lagged one is close to zero. To understand this, assume that there were initially 10 workers in manufacturing. Suppose that there is a positive shock to yield in year t, and one worker moved from agriculture to manufacturing after the harvest in the same year t and continued to work in manufacturing until the next year, $t+1$, before the next harvest. Now, the number of employees in manufacturing is 11 both at t and $t+1$, while it is still 10 at time $t-1$. Thus, log employment growth is $log(11/10) > 0$ at time t while it is $log(11/11) = 0$ at time $t+1$. This example explains why the coefficient on current year yield growth is significantly positive, while the coefficient on the lagged one is close to zero. The bottom line is that the agricultural workers in the Northern Hemisphere move to manufacturing after the harvest and before the new calendar year starts, which leads to the significantly positive

[24] It is possible that the resource reallocation effect still exists in countries near the equator. Another reason for the insignificant estimation result might be that the agricultural seasonality near the equator may not be well aligned with the annual calendar data (for example, it is probable that rainfall from previous year June to next year March affects crop yields that are mostly harvested in May).

estimates for the coefficient on the current year yield growth (and the close-to-zero estimates for the lagged one).

Table 10 displays sector-specific regression results (total eight sectors, see Table A.2 for the description) in developing countries, with the same estimation structure as the specification 7 of Table 9. Interestingly, the wood product industries, which are highly labor-intensive, exhibit a highly significant effect: a 10% decrease in agricultural productivity results in a 5.5% decrease in the number of employees, which is statistically significant at the 1% level. On the other hand, highly capital-intensive industries such as chemicals, electrical machinery, and motor vehicles register insignificantly. A plausible explanation is that capital-intensive industries have an incentive to keep their workers, because costly capital assets need to be operated continuously to cover the cost. Meanwhile, the employment in textiles registers insignificantly despite its labor intensiveness, possibly due to the high share of exports.

Capital investment allocations — Table 11 displays the results of estimating Equation (13), which explores the relationship between crop yield and capital investment in manufacturing. The IV result in column 2 implies that a 1% decrease in crop yield in year t leads to about 1.7% decrease in capital investment in manufacturing in developing countries (per capita income less than \$10,000) in both years t and $t+1$. Comparing with the column 1 result shows the downward bias of the OLS result. This pattern is consistent with the previous results on output and employment. These results support the theoretical mechanism that some capital reallocates out of manufacturing in response to a decrease in agricultural productivity.[25] Admittedly, I do not directly observe capital stock moving into agriculture. However, if we consider new capital investments that are available in the economy each year, a decrease in investment in manufacturing can be interpreted as more investments in agriculture (assuming that new capital investments are independent of agricultural productivity).[26] When the sample is further restricted to the ones that are relatively closed to trade (the export share in manufacturing output less than 20%), the effect becomes larger. On the other hand, I find that the positive link becomes insignificant when the country is relatively more open to trade or when the level of income is higher (per capita income greater than \$15,000), which is consistent with the theory.

Table 12 shows sector-specific regression results. I find that capital investments in capital-intensive sectors (industries related to electrical machinery, basic metals and equipment) are highly responsive to changes in agricultural productivity in developing countries. Meanwhile, the wood-products industry (sector 3), which is labor intensive, registers insignificantly. Recall that in Table 10 the effect on employment was large and highly significant for the wood-products industry, while other capital-intensive industries registered insignificantly. This

[25]It will be ideal if one can show with data that more resources reallocate toward agriculture in response to an exogenous decrease in yield. However, agricultural data on resources does not have enough accuracy to track year-to-year changes as the majority of agricultural land is managed by individuals or families in developing countries.

[26]Another plausible channel that is not implied by the theory is that the total amount of new investments decreases after an adverse shock to agricultural productivity, which will also reduce investment in manufacturing.

flipping of results implies that the factor intensity of manufacturing sectors may determine what type of factors move more intensively in response to agricultural productivity shocks, which strengthens the robustness of the results in support of the theoretical mechanism.

5.4 Robustness

Estimations with Longer Lags — So far, all the estimating equations have included only the current year and the previous year crop yield growth rates instrumented by rainfall. There are two important reasons for this. First, rainfall at a longer lag does not significantly affect the outcome variables. As will be shown in this section, the effect of rainfall shocks on manufacturing does not persist more than two years. Although a harsh drought may affect manufacturing for a longer period of time, various econometric estimations do not seem to capture these cases. Second, growth rates over time are serially correlated, as the denominator of a growth rate in year t is exactly the same as the numerator of the rate in year $t-1$. In particular, such correlations are even more problematic for rainfall growth rates, as one of two years of drought are likely to be followed by more rainfall the next year, for example. Therefore, including unnecessary lags of rainfall growth may distort the estimates of the coefficients that truly matter.

In this section, I include longer lags of rainfall shocks in several different forms, and see how many years the impact of such shocks persists. Tables 13-18 present estimation results when the log growth rates of manufacturing employment and output are regressed on up to 10 lags of rainfall shocks in three different forms: drought dummies, log levels of rainfall, and crop yields instrumented by rainfall (in log growth rates). All the estimations are performed on the sample restricted to the less developed countries in the Northern Hemisphere (per capita income less than \$10,000 and 10-degrees minimum latitude cutoff).

Table 13 shows how rainfall shortages directly affect manufacturing employment over time. The estimating equation is the following:

$$\Delta L^m_{c,t} = \alpha_c + \alpha_t + \beta + \Sigma_{j=0}^{10} \beta_j \cdot drought_{c,t-j} + \epsilon_{c,t} \ , \tag{15}$$

where $drought_{c,t-j}$ is a dummy variable which takes 1 if the precipitation of the country c in the year $t-j$ is less than 90% of the average precipitation over time in the country; $\Delta L^m_{c,t} = ln \frac{L^m_{c,t}}{L^m_{c,t-1}}$; α_c is a country fixed effect; α_t is a time-fixed effect; $\epsilon_{c,t}$ is an idiosyncratic error term. Table 13 presents the estimation results, with the four varying sample restrictions which are in line with the ones in Table 9. Comparing the results of columns 1-4 of Table 13 reveals that the coefficients on the current year t drought dummy are all negative and highly significant. These are consistent with the main results in Table 9 which show that a decrease in the current year yield induced by rainfall shortages leads to a reduction in manufacturing employment.

Meanwhile, the coefficients on the 1-year-lagged drought dummy are all positive, the opposite sign, and the t-statistics vary from 2.30 to 1.55 (row 2 of Table 13). Note that the rainfall shortage in year $t-1$ can affect the manufacturing employment growth rate in year

t, $ln\frac{L^m_{c,t}}{L^m_{c,t-1}}$, in two opposite directions: (i) reducing the denominator $L^m_{c,t-1}$, as the rainfall shortage reduces the manufacturing employment in the same year, thus increasing $ln\frac{L^m_{c,t}}{L^m_{c,t-1}}$; (ii) reducing the numerator $L^m_{c,t}$, if the rainfall shortage effect persists longer, thus decreasing $ln\frac{L^m_{c,t}}{L^m_{c,t-1}}$. Therefore, the positive signs of the estimates imply that the rainfall shortage in the year $t-1$ predominantly reduced the same year employment $L^m_{c,t-1}$ rather than the following year employment. Now, the question is, for how many years does a rainfall shortage affect employment in manufacturing? Observing the nine remaining coefficients on the drought dummies from $t-2$ to $t-10$ for the four specifications in Table 13, we notice that 35 out of 36 estimates are not statistically significant with magnitudes near zero. This implies that the effect of rainfall shortages on labor movement does not persist more than two years.

For poorer and more credit constrained countries (columns 2-3 of Table 13), a rainfall shortage (having less than 90% of average precipitation) in the current year t reduces the manufacturing employment growth by about 4%, while a rainfall shortage in the previous year $t-1$ leads to about 7% increase of the growth rate. Similar results hold for the specification with no further restriction (column 1) and for the higher latitude countries (column 4), with each magnitude of the effects decreased by about 2 percentage points. The bottom line is that the larger estimates for the poorer and more credit constrained countries are consistent with the main results in Table 9.

Next, to generate results in Table 14, I replace the drought dummies with log precipitation levels in the above Equation (15). For each of the four sample restrictions, I report both results with 3 lags and 10 lags. For a fair comparison, I drop the initial 10 years of observations to equalize the number of observations. The pattern of results is similar to the Table 13 results described above: (i) rainfall shortages in the current (previous) year lead to a reduction (an increase) in manufacturing employment; (ii) the coefficients for the lagged rainfall from $t-2$ to $t-10$ are not statistically significant and are mostly close to zero; and (iii) the estimates are larger for poorer and more credit constrained countries. In addition, the estimates with 10 lags are somewhat smaller than the ones with 3 lags (first row of Table 14). If we believe the estimation results that the rainfall shocks occurred more than 4 years in advance have no statistically significant effects, the discrepancies between the results of the two specifications with 3 lags and 10 lags may be attributable to the correlation among the lagged rainfall variables themselves. For example, rainfall shortages for one or two years are likely to be followed by more rainfall the next year.

Such serial correlations across the lags are even more problematic when the estimations involve long lags of growth rates in rainfall, as the denominator of a growth rate in year t is equal to the numerator of the rate in year $t-1$. Not surprisingly, the original estimation results (Table 9) become highly distorted when I include 10 lags of the yield growth rates instrumented by rainfall growth. However, Table 15 shows that the results are fairly robust to the inclusion of up to 3 lags.

So far, I have investigated the results of the three variants of the empirical framework associated with employment. Now, I repeat the same robustness checks for manufacturing output specifications. Table 16 shows the output results with the 10 lags of the drought dummies. Recall that the dependent variable is the manufacturing output growth rate in year t, $ln\frac{q^m_{c,t}}{q^m_{c,t-1}}$. The drought dummies can affect the growth rate by affecting $q^m_{c,t}$, $q^m_{c,t-1}$, or both. First, the coefficients on the drought dummy in year $t-2$ are significant and have positive signs. Similar results hold for the coefficients of the $t-3$ drought dummy. This implies that the rainfall shortages in years $t-2$ and $t-3$ decrease the output in year $t-1$, thus raising the year t output growth rate. Put differently, there exists up to two years of time lag between rainfall shocks and manufacturing production. Second, the coefficients on the drought dummies from $t-4$ to $t-10$ are mostly close to zero and statistically not significant, implying that the effect of rainfall shortages does not persist for more than two years (as the rainfall shock in $t-4$ has no effect on output in $t-1$). Third, the coefficients on the current year t drought dummy are all negative, and these are statistically significant for low-income countries, countries that are relatively closed to trade, and the ones with large agricultural production shares (columns 2-4 of Table 16). Note that the only way for the current year drought to decrease the current year output growth rate is by reducing the current year output $q^m_{c,t}$. Lastly, the coefficients on the drought dummy in year $t-1$ are all negative, although not statistically significant. A plausible reason is that the rainfall shortage in year $t-1$ could have affected both $q^m_{c,t}$ and $q^m_{c,t-1}$, with more weight on the following calendar year output, $q^m_{c,t}$.

Similarly, Table 17 shows that the coefficients on the log precipitation levels in year $t-2$ are negative and statistically significant. More rainfall in year $t-2$ raises output in $t-1$, thus decreasing the output growth rate in year t. On the other hand, more rainfall in year $t-1$ may increase output both in year $t-1$ and in the year t, leading to the statistically not significant estimates for the year $t-1$ coefficient. Meanwhile, unlike the results in Table 16, the coefficients on the log precipitation in year $t-3$ are not significant. It seems that the drought dummy is able to capture more persistent effects on output than the continuous precipitation level variable. Finally, in Table 18, I turn to the original main estimations on output and include up to three lags of yield growth rates instrumented by rainfall growth. The results are reasonably robust to the previous results displayed in Tables 7 and 8. As mentioned above, some discrepancies across the results with the differing number of lags are likely to be caused by the strong correlations among the lags of the rainfall and yield growth rates.

Poor Countries' Data Quality — There exist concerns about the quality of rainfall and crop yield data in poor countries. First, Dell, Jones, and Olken (2012) show that their estimations of the weather effect on economic growth using a number of different weather datasets lead to similar results. They also find that there is no relationship between a country's economic conditions and the number of weather stations actually reporting the weather in a given year. Second, there is a particular concern that some poor countries may directly use rainfall data to produce crop yield data. If this is the case, one can expect that the elasticity of crop yield with respect to rainfall for low-income countries will be close to one or a value that is very different from the elasticity for higher income countries. However, column 1 of Table 6 shows that such elasticity is 0.42 for the Sub-Saharan African countries, compared to 0.20 for the less developed countries (GDP per capita less than $10,000) excluding Sub-Saharan Africa (column 4 of Table 6). Given the dry weather and poor irrigation systems in many Sub-Saharan African countries, such difference between the two elasticities seems reasonable. In addition, the elasticity is 0.25 for the less developed countries with minimum latitude 10 degrees in the Northern Hemisphere, which automatically excludes many Sub-Saharan African countries (column 5 of Table 6). Furthermore, the corresponding t-statistics of the three estimates are not much different from one another at around 7.

Third, I test whether the main estimation results on the relationship between yield and manufacturing output are robust to the exclusion of low quality data. Columns 4 and 6 of Table 7 show the IV results with the $2,000 minimum income cutoff and the exclusion of the Sub-Saharan African countries, respectively. Both of the estimates of the lagged yield growth coefficients are statistically significant at the 5% level, with the correct sign and similar magnitudes as other estimates of the various specifications reported in Tables 7 and 8.[27] Moreover, I find that the employment result (the effect of yield on employment in manufacturing, discussed in section 5.3) is also robust to the exclusion of the Sub-Saharan African countries (column 3 of Table 9) and the exclusion of countries with per capita income less than $2,000.

5.5 Crop Prices and International Trade in Agriculture

Domestic productivity shocks and domestic crop prices — Recall that the price channel links between agricultural productivity shocks and resource reallocations: a negative shock to agricultural productivity causes food prices to go up, and resources move toward agriculture. The negative link between productivity and food prices is stronger when the economy is relatively closed to agricultural trade. Indeed, there is a large literature showing limited international price transmission to domestic food markets due to various trade barriers in agriculture (e.g., Anderson and Nelgen, 2012; Atkin, 2012; Gollin and Rogerson, 2014). Accordingly, the econometric estimation results in Table A.4 confirms that negative shocks to productivity tend to raise crop prices. For instance, I find that a 10% decrease in yield induced by rainfall shortages leads to roughly an 8% increase in wheat and barley prices.[28] Both results are highly significant at the 1% level. Results for maize, sorghum, and soybean prices also display consistent results at the 5% level of significance. In sum,

[27] Column 3 of Table 7 shows that the IV estimation result of the elasticity of manufacturing output with respect to crop yield is 0.18, when the sample is restricted to less developed countries with the 10-degree minimum latitude in the Northern Hemisphere. When the sample is further restricted with the $2,000 minimum income cutoff, the elasticity increases to 0.24 (column 4 of Table 7). This may be because the poorest countries tend to be located close to the Equator, where agricultural workers have low incentive to move to other sectors as the harvest takes place all year round. Similarly, the column 6 result can be compared to column 2 of Table 7 which excludes the Sub-Saharan African countries.

[28] Yields in the estimations in Table A.4 are not crop specific and include all major staple crops as described in 4.2. This is for the purpose of allowing substitution effects. For example, when overall yields of major staple crops fall, the price of maize can rise due to the substitution effect even if maize yield did not change.

these results suggest that short-run fluctuations in crop prices are significantly affected by domestic productivity shocks.

Brief remarks on international trade in agriculture — Although agricultural trade is an important factor, it has not been taken into consideration in the data analysis so far. I instead have used trade data only in manufacturing as a measure for openness to trade for its simplicity. Note that agricultural imports and exports may affect the model predictions differently. For example, in countries with large shares of agricultural imports, the domestic food prices will heavily depend on international prices, thus weakening the positive link between yields and manufacturing output. On the other hand, for countries with intensive agricultural exports, an increase in agricultural productivity raises total income (due to an increase in agriculture exports), which can cause manufacturing output to rise due to positive income effects (thus, strengthening the positive link). Although I find some empirical evidence that supports these predictions, it is difficult to clearly identify the role of agricultural imports and exports separately. This is simply because countries engage in both importing and exporting agricultural goods, and governments impose barriers to agricultural trade – possibly depending on domestic productivity or international food price shocks – in order to protect domestic markets. Thus, I instead present open economy models in the following section, and theoretically show that higher openness to trade weakens the income effect and helps resources reallocate toward relatively more productive sectors.

6 Open Economy

As discussed above, the key in applying the baseline model to the real world is whether domestic agricultural productivity shocks affect domestic prices, or are absorbed through changes in trade volumes. To further investigate this, I extend the baseline model and present two versions of open-economy models. First, using a two-country model, I show that the link between agricultural productivity and manufacturing output in home country changes sign from positive to negative as the size of foreign country increases. Second, using a model that allows imperfect pass-through of international food prices to the domestic market, I show that the effect of domestic productivity shocks is attenuated and matches the magnitude that was found in the previous econometric estimation (recall that the elasticity of manufacturing output with respect to agricultural productivity implied by the baseline model was more than twice higher).

6.1 Two-Country Model

Assume a world economy consisting of two countries of the baseline model type, indexed by $c = H, F$. The two countries are identical except for population and agricultural productivity. They produce homogenous manufacturing and agricultural goods, and engage in free trade with no transportation costs. In country c there exists L_c population, each endowed with one unit of labor and $\frac{K_c}{L_c}$ units of capital. In this subsection, we focus on how the home country's equilibrium allocations are affected by domestic agricultural productivity shocks, while varying the size of the foreign country.

On the demand side, each agent in both countries has the following Stone-Geary preference:

$$u = (q_a - \gamma_a)^{\alpha} q_m^{1-\alpha}, \qquad 0 < \alpha < 1.$$

Accordingly, the aggregate preference for country c with total population L_c is:

$$U_c = L_c \cdot (q_a - \gamma_a)^{\alpha} q_m^{1-\alpha} = (L_c q_a - L_c \gamma_a)^{\alpha} (L_c q_m)^{1-\alpha}.$$

Rewriting $L_c q_a$ and $L_c q_m$ as $q_{a,c}$ and $q_{m,c}$, we have

$$U_c = (q_{a,c} - L_c \gamma_a)^{\alpha} q_{m,c}^{1-\alpha}, \quad c = H, F.$$

Given the aggregate preferences, we can solve the utility maximization problems for each country as if there were one representative agent.

The production side has the same setting as described in section 2. Labor and capital are perfectly mobile between the two sectors within a country, but not across the countries. Since goods are freely traded with zero transport costs, there will be one relative equilibrium price p_a across countries. The competitive equilibrium of the open economy model is a set of allocations $\{L_{a,c}, L_{m,c}, K_{a,c}, K_{m,c}, q_{a,c}, q_{m,c}\}$ and prices $\{p_a, w_c, r_c\}$, such that, given prices, (1) $\{q_{a,c}, q_{m,c}\}$ solve the utility maximization problem of the representative agent, (2) $\{L_{a,c}, L_{m,c}, K_{a,c}, K_{m,c}\}$ solve the profit maximization problem of each sector, and (3) all markets clear internationally (i.e., for each sector, the sum of produced quantity in the world equals the sum of demand in the world).

Quantitative analysis — Given the equilibrium solutions (see Appendix A.3 for the derivation), the key question is, how does the model prediction for the home country change as the size of the foreign country varies? To address this question, I simulate the model and investigate how an agricultural shock in the home country affects resource reallocations differently depending on the size of the foreign country. For simplicity, we assume there is a constant C that satisfies $L_F = C \cdot L_H$ and $K_F = C \cdot K_H$. Thus, C indicates the factor by which the foreign country is bigger than the home country.

The same calibrated parameters are applied for purpose of comparison (see Table 1), and, initially, both countries are identical in all aspects except the population.[29] Table A.5 shows changes in equilibrium allocations when the home country is subject to a 15% decrease in agricultural productivity. The first two columns of the table show that for $C = 0.01, 0.20$, and 0.25 agricultural employment has positive growth, whereas manufacturing employment has negative growth. The dominating income effect leads to the perverse phenomenon in which resources are moving toward a sector with declining productivity. However, the strength of the positive link between agricultural productivity and manufacturing output weakens as the foreign country size increases, and eventually the link changes sign. The last three rows

[29] Both home and foreign countries are set as Ethiopia where capital stock, agricultural productivity, and manufacturing productivity are all equal to 1.

show that resources flow in the opposite direction: for $C = 0.30, 0.35$, and 0.50, some labor moves out of agriculture and into manufacturing, which results in increases in manufacturing output.

What affects the sign and the strength of the link between agricultural productivity and manufacturing? There are two competing effects in this model: (1) the income effect, which causes a positive link and (2) the comparative advantage effect, which causes a negative link. The income effect is strongest under the closed economy. In contrast, the comparative advantage effect is strongest under the small open economy, as is explained in the following subsection.

Comparative advantage effects under the small open economy — The comparative advantage effect can be easily identified algebraically under the small open economy rather than in the two-country model. Thus, imagine a small open economy where world prices of the goods are fixed. Since these prices are fixed, the demand system has no effect on production, so the resource allocations and manufacturing output will be solely determined by the supply side. Appendix A.3 derives a closed form solution for L_m under the small open economy assumption with fixed world prices $p_a = p_w$ as follows:

$$L_m = \left(\frac{z_m}{z_a} \cdot \frac{\lambda_3}{p_w}\right)^{\frac{1}{\beta_m - \beta_a}} \cdot \frac{K}{\beta_m - \beta_a} - \frac{\beta_a(1-\beta_m)}{\beta_m - \beta_a} \cdot L \ , \tag{16}$$

where $\lambda_3 = \frac{\beta_m}{\beta_a}[\beta_m(1-\beta_a)]^{\beta_m - 1}[\beta_a(1-\beta_m)]^{1-\beta_a}$. Note that L_m is positively correlated with relative productivity $\frac{z_m}{z_a}$. When agricultural productivity z_a decreases, the manufacturing sector becomes relatively more productive, so some labor and capital resources move toward manufacturing and out of agriculture for profits (thus, a negative link between agricultural productivity and manufacturing output).

6.2 Imperfect Pass-through Model

The model in this section is motivated by the literature on agricultural trade that studies the imperfect pass-through of international food prices to domestic food prices. For example, Anderson and Nelgen (2012) show that the unweighted average of the short run elasticity of international price transmission to domestic markets (for rice, wheat, and maize) is 0.52.[30] In other words, a 1% increase in international prices leads to only a 0.52% – not 1% – increase in domestic prices.[31] Note that this phenomenon is closely associated with the fact that the share of traded goods in agriculture is low. For example, less than 8% of rice production and less than 20% of wheat production are traded in the world according to USDA (2012). There might be several reasons for this: (1) biased consumer preferences

[30] They use a partial-adjustment geometric distributed lag formulation to estimate elasticities for each key product for 75 countries for the period 1985-2004. The short run price elasticity is for changes within a year, while the long run elasticity is for changes over three to five years.

[31] This finding is consistent with the literature showing that the domestic supply shock is the main contributing factor for short run food price fluctuations, while long run fluctuations are primarily attributed to international prices or exchange rates (Loening et al., 2009; Burgess et al., 2011; Anderson and Nelgen, 2012).

for locally abundant foods (Atkin, 2012), (2) high transportation costs, as food is bulky and heavy (Tombe, 2015; Gollin and Rogerson, 2014; Caselli, Chen, Gollin, 2012), and (3) governments imposing barriers to agricultural trade in order to protect domestic markets from international price variability (e.g., Anderson and Nelgen, 2012; Gouel, 2012; Martin and Anderson, 2012). In other words, in the real world with costly trade, a combination of low agricultural trade volumes and explicit protection of domestic agricultural markets leads to imperfect pass-through of international prices. Hence, domestic supply and demand still play a crucial role in determining equilibrium prices and output. Accordingly, while the direction of the baseline model (closed economy) results might still hold, the magnitudes of the effects will be attenuated in the presence of international markets.

In the two-country model, the domestic productivity shock was 'fully' translated into a combination of the two competing effects: an income effect and a comparative advantage effect. This section introduces a model in which domestic agricultural productivity has only a 'partial' impact. The primary difference in the model setting compared to the two-country model is that foreign foods enter the model as imperfect substitutes for home foods, which is associated with the above explanation by Atkin (2012). This allows fitting the model to the empirical observation on the imperfect pass-through of international food prices.

In this section, I assume a small open economy that imports foods and exports manufactures. Although this assumption is for algebraic simplicity, it can be somewhat justified given the fact that 111 out of 136 developing countries were net food importers during 2005 - 2009 (FAOSTAT).[32] In addition, I assume homogenous manufacturing products whose prices are normalized to one, while agricultural goods are differentiated depending on the country of origin. Also, I assume that agricultural goods from the world can be inelastically supplied to the home country at the fixed world price $p_{a,w}$. Lastly, I assume balanced trade in which the value of agricultural imports equals that of manufacturing exports.

A representative agent has a preference represented by Cobb-Douglas Stone-Geary upper-tier utility and CES lower-tier utility,

$$U = ([q_a^{\frac{\sigma-1}{\sigma}} + q_{a,w}^{\frac{\sigma-1}{\sigma}}]^{\frac{\sigma}{\sigma-1}} - \gamma_a)^{\alpha} q_m^{1-\alpha}, \tag{17}$$

where $q_{a,w}$ denotes agricultural goods that are produced in the world, and q_a and q_m are domestically produced agricultural and manufacturing goods. Given the prices, the agent maximizes the utility subject to the budget constraint $I = wL + rK = p_a q_a + p_{a,w} q_{a,w} + q_m$. The demand functions for manufacturing, domestic agricultural goods, and agricultural imports from the world are the following:

$$q_m = (1-\alpha) \cdot (I - \overline{p_a}\gamma_a), \tag{18}$$

$$q_a = \frac{p_a^{-\sigma}}{p_a^{1-\sigma} + p_{a,w}^{1-\sigma}} \cdot [\alpha(I - \overline{p_a}\gamma_a) + \overline{p_a}\gamma_a], \tag{19}$$

[32]If domestic food can be exported, then the world demand for the domestic food will affect the domestic price. This requires a two-country model, which will only complicate the model without producing much information, since most developing countries are small open economies and net food importers.

$$q_{a,w}^{imp} = \frac{p_{a,w}^{-\sigma}}{p_a^{1-\sigma} + p_{a,w}^{1-\sigma}} \cdot [\alpha(I - \overline{p_a}\gamma_a) + \overline{p_a}\gamma_a], \tag{20}$$

where $\overline{p_a} = (p_a^{1-\sigma} + p_{a,w}^{1-\sigma})^{1/(1-\sigma)}$, which is the domestic agricultural price index.

The supply side takes the same Cobb-Dougals technology setting as the previous models. The balanced trade condition implies that $p_{a,w} q_{a,w}^{imp} = q_m^{exp}$. In addition, the market clearing condition implies that

$$z_m K_m^{\beta_m} L_m^{1-\beta_m} = q_m + \underbrace{p_{a,w} q_{a,w}^{imp}}_{q_m^{exp}}. \tag{21}$$

Using first-order conditions derived from the production side, I can express p_a, K_m, w, and r in terms of L_m and other parameters. Using this and by plugging Equations (18) and (20) into Equation (21), I obtain an implicit solution for L_m.

There are two competing effects in this model in response to a decrease in domestic agricultural productivity (thus an increase in the domestic agricultural price). First, since the foreign agricultural goods are only imperfect substitutes for domestic products, the domestic food price index $\overline{p_a} = (p_a^{1-\sigma} + p_{a,w}^{1-\sigma})^{1/(1-\sigma)}$ will still increase, thus reducing the disposable income $I - \overline{p_a}\gamma_a$. However, the magnitude of the price increase will be smaller than the price increase in the baseline model. This leads to an income effect whose magnitude is smaller compared to the baseline model. Second, due to the increase in the domestic food price, some consumers substitute away from domestic foods for more foreign foods. Therefore, on the production side, more resources will be allocated toward manufacturing because of the decreasing demand in domestic agricultural goods. Among the two competing effects, the following calibration result shows that the income effect still dominates, but the strength of the link is much weaker compared to the baseline model.

While all other parameters are set at the previously calibrated values shown in Table 1, σ is newly calibrated based on the estimation result by Anderson and Nelgen (2012), who show that the un-weighted average of the short run elasticity of international price transmission to domestic markets (for rice, wheat, and maize) is 0.52. I calibrate σ in such a way that a 1% increase in the world price $p_{a,w}$ leads to a 0.52% increase in the equilibrium domestic price index $\overline{p_a} = (p_a^{1-\sigma} + p_{a,w}^{1-\sigma})^{1/(1-\sigma)}$. This gives $\sigma \approx 5$. For simple comparison, I fix the world price $p_{a,w}$ at the equilibrium price of the baseline model, and $z_{a,c}$ takes the average value of crop yields in country c.

Given the parameter values, I re-simulate this model and investigate changes in manufacturing output in response to a 15% decrease in domestic agricultural productivity. Column 5 of Table 4 shows that magnitudes of growth rates are much smaller than the baseline model results in column 1 – for example, in Ghana this model generates a 4.8% decrease in output, whereas the baseline model generates a 17.2% decrease. This leads to a much closer match to the econometric estimation result in the previous section, which predicts about a 4.4% decrease in output (in response to the -15% productivity shock) for developing countries (column 2 in Table 8).

7 Concluding Remarks

This paper identified a novel mechanism by which agricultural productivity shocks affect industrial output through general equilibrium linkages. In the baseline model, adverse shocks to agricultural productivity require that increased labor and capital resources be devoted to agriculture to meet the subsistence requirement. As resources available to manufacturing fall, so does manufacturing output. Both the calibration exercise and econometric estimations show that the strength of the positive link between agricultural productivity and manufacturing output decreases with income level, and that the degree of output fluctuations also decreases with income level.

These findings have important implications for development and international trade. First, this paper shows that adverse shocks to agriculture add considerable uncertainty to manufacturing sectors in developing countries, a feature which may push investors away and dampen economic growth. Second, the subsistence requirement feature leads to a counterintuitive situation: resources flow toward the sector with declining productivity. I have demonstrated that this may worsen aggregate productivity in developing countries. Fortunately, the open economy models suggest a clear solution that international trade, especially in agriculture, can help mitigate the impact of agricultural shocks on developing economies. As an example, under the small open economy, resources can move to any sector that has become relatively more productive even in the presence of subsistence consumption. Thus, an economic loss caused by a decrease in agricultural productivity is not only limited to agriculture but also partly offset by producing more manufactures.

The implication for international food trade is relevant in light of recent developments. First, researchers have shown that climate change will increase temperature and the frequency and severity of droughts. Unfortunately, developing countries will suffer the most, as many of them are located near the Equator where further increases in temperature can significantly lower agricultural productivity (e.g., Lobell and Field, 2007; Burgess, Deschenes, Donaldson, and Greenstone, 2013). Second, after the 2007-2008 world food crisis (during which, for example, international prices for rice increased by 160% within a year), countries have tried to insulate domestic markets from international price variability by restricting food exports and relying on self-sufficiency. This paper suggests that such policies are likely to increase output fluctuations in poor countries and sheds light on the importance of reestablishing a reliable world market for food.

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Figures and Tables

Table 1 Calibration of Parameter Values

Parameter	Value	Comments	Data source
$\boldsymbol{K_c}$	[1, 90.8]	Per capita capital stock of each country normalized by Ethiopia's	Investment data, Penn World Table 7.1
$\boldsymbol{L}$	1	Normalization	
$\boldsymbol{\beta_m}$	0.58	Capital income share in manufacturing (Cobb-Douglas production parameter)	GTAP Input-Output table (India 2007)
$\boldsymbol{\beta_a}$	0.32	Capital income share in agriculture (Cobb-Douglas production parameter)	GTAP Input-Output table (India 2007)
$\boldsymbol{z_{m,c}}$	[1, 5.12]	Free parameter which is set to match each country's income excluding service sectors	World Bank (2004)
$\boldsymbol{z_{a,c}^t}$	[1, 7.64]	Yearly crop yields of each country normalized by Ethiopia's minimum yield	FAO (1970 – 2002)
$\boldsymbol{\alpha}$	0.0178	Utility weight parameter	Used the equilibrium solution equation (9) and employment shares in manufacturing in the U.S. = 0.91 and in Ethiopia = 0.07 (WB, 2004))
$\boldsymbol{\gamma_a}$	0.8910	Utility subsistence parameter	

Notes: Values in brackets represent ranges of country or time specific parameters (c denotes a country, t denotes a year). Ethiopia serves as a base country, as it is one of the poorest countries in the manufacturing data provided by UNIDO (2011).

Table 2 Changes in Manufacturing Output
(A 15% decrease in agricultural productivity)

Country	K	$z_{a,c}$	$\frac{p_a^* \gamma_a}{I^*}$	L_m^*	z_a decreases by 15%			
					$\%\Delta p_a^*$	$\%\Delta L_m^*$	$\%\Delta K_m^*$	$\%\Delta q_m^*$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ethiopia	1.00	1.00	0.89	0.07	+ 22.4%	- 58.0%	- 51.1%	- 54.2%
Malawi	2.14	1.19	0.57	0.31	+ 20.6%	- 21.9%	- 13.0%	- 16.4%
Ghana	3.00	1.04	0.58	0.30	+ 20.6%	- 21.8%	- 13.8%	- 17.2%
Bangladesh	2.84	2.36	0.25	0.63	+ 18.9%	- 6.9%	- 3.1%	- 4.7%
India	6.17	1.73	0.27	0.61	+ 19.0%	- 7.4%	- 3.4%	- 5.1%
Portugal	60.76	1.77	0.12	0.79	+ 18.2%	- 3.1%	- 1.2%	- 2.0%
United States	90.84	4.59	0.04	0.91	+ 17.8%	- 1.0%	- 0.4%	- 0.6%

Notes: * indicates that it is an equilibrium outcome from the simulation of the baseline model. $z_{a,c}$ denotes the average value of cereal yields over the period 1970-2002 in a country c, normalized by Ethiopia's.

Table 3 Simulated Volatility

Country	(Data) Crop yield volatility (1)	Simulated manuf. output volatility (2)	(Data) Manuf. output volatility (3)
Ethiopia	12.9%	40.7%	18.9%
Malawi	45.8%	65.1%	16.5%
Ghana	19.5%	79.1%	45.2%
Bangladesh	5.6%	2.6%	25.8%
India	6.4%	3.3%	10.5%
Portugal	16.6%	2.8%	14.7%
United States	13.6%	0.6%	5.0%

Notes: The simulated volatility values (column 2) of the baseline model are based on the annual yield data from the FAO (see Table 1). Values in columns 1 and 3 are computed directly from the data. Volatility in percentage terms can be understood simply as the standard deviation of percentage changes in output.

Table 4 Model Extensions

Country	$\%\Delta q_m^*$ (z_a decreases by 15%)				
	Baseline model (σ = 1)	CES model			Imperfect pass-through model
		σ = 0.52	σ = 0.85	σ = 2.5	
	(1)	(2)	(3)	(4)	(5)
Ethiopia	- 54.162%	-54.653%	-54.207%	- 54.161%	- 11.808%
Malawi	- 16.429%	-17.121%	-16.5%	-16.427%	- 4.664%
Ghana	- 17.235%	-18.441%	-17.32%	- 17.234%	- 4.834%
Bangladesh	- 4.73%	-5.378%	-4.802%	- 4.727%	- 1.499%
India	- 5.145%	-6.051%	-5.225%	- 5.144%	- 1.622%
Portugal	- 2.032%	-3.46%	-2.125%	- 2.032%	- .665%
United States	- .627%	-1.711%	-0.711%	- .626%	- .209%

Table 5 Descriptive Statistics

	Mean of cross-country values				
	All countries		GDP per capita < 4000	GDP per capita > 10000	
	Mean	Stand. Dev.	Stand. Dev. / (*) = Mean		Observations (all countries)
	(1)	(2)	(3)	(4)	
Manufacturing :					
1. Growth of output (value added)	1.06	.20	.25	.14	2,047
2. Growth of number of employees	1.03	.12	.16	.07	2,344
3. Growth of gross capital formation	1.25	.66	.98	.25	1,449
Agriculture :					
4. Growth of crop-area rainfall	1.03	.22	.23	.23	3,776
5. Growth of cereal yield	1.05	.22	.26	.16	3,391
6. Growth of wheat price	1.09	.40	.69	.23	1,110
7. Growth of maize price	1.13	.38	.31	.23	1,287
8. Growth of rice price	1.14	.45	.41	.21	969
9. Share of agriculture (% of GDP)	19.7	4.0	31.0*	5.5*	2,977
Other variables:					
10. Growth of GDP per capita	1.02	.06	.07	.04	3,379
11. Growth of exchange rate to $US	2.88	7.20	12.54	.27	3,447
12. Export share in manufacturing output	.37	.23	.40*	.24*	2,217
13. Private credit (% of GDP)	32	9.6	18*	64*	2,590

Notes: The data above have country-year observations. Columns 1-4 report mean of cross country average values. Column 3 is for countries with per capita GDP less than $4,000 (in 2005 international dollars), and column 4 is for higher income countries. The sample refers to the years 1970-2002, except the crop prices which refer to 1991-2008 due to limited availability.

Table 6 Rainfall and Crop Yield (First-stage results)

	Dependent variable: Crop yield, t (in log growth rates)					
	Sub-Saharan Africa only	GDP per capita < $4,000	GDP per capita < $10,000			GDP per capita > $10,000
				Sub-Saharan Africa Excluded	Northern hemisphere	
	(1)	(2)	(3)	(4)	(5)	(6)
LogRainfallGrowth, t	.42*** [7.63]	.34*** [10.74]	.28*** [11.25]	.20*** [7.48]	.25*** [7.75]	.07** [2.46]
TropicalRegion × LogRainfallGrowth,t	-.56 [-1.36]	-.36*** [-4.62]	-.25*** [-4.74]	-.16*** [-3.16]	-.18** [-2.09]	-.33 [-1.41]
LogRainfallGrowth,t-1	-.01 [-.24]	.01 [.24]	.01 [.27]	-.01 [-.25]	-.01 [-.42]	.06** [2.16]
TropicalRegion × LogRainfallGrowth,t-1	-.07 [-.15]	-.04 [-.53]	.00 [.01]	.03 [.56]	.00 [.03]	-.03 [-.12]
R-squared	.19	.13	.10	.08	.11	.10
F-statistics	23.77	38.98	44.43	22.61	25.94	1.73
Observations	764	1,609	2400	1,636	1,259	852

Notes: T-statistics are in brackets. Each observation is a country-year. 'Northern hemisphere' represents the countries with latitude greater than 10. Each regression includes country and year fixed effects.
*** p < 0.01, ** p < 0.05, * p < 0.1.

Table 7 Manufacturing Output and Crop Yield (instrumented with rainfall)

	Dependent variable: Manufacturing output, t (in log growth)								
	GDP per capita < $10,000							GDP per capita < $4,000	GDP per capita > $10,000
	all		Northern hemisphere		Northern hemisphere*	Sub-Saharan Africa Excluded	Equator	Northern hemisphere	Northern hemisphere
			all	GDP per capita > $2,000					
	OLS	IV	IV	IV	IV	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log yield growth, t-1	.08**	.19**	.18**	.24**	.26**	.29**	.20	.24**	.39
	[2.37]	[2.05]	[2.33]	[2.17]	[2.24]	[2.10]	[1.20]	[2.43]	[.15]
Log yield growth, t	.08*	-.00	.02	.28	.15	.10	-.16	.05	-.35
	[1.83]	[.13]	[.13]	[1.41]	[.65]	[.35]	[-.61]	[.24]	[-.23]
Log exchange rate growth, t	-.16***	-.16***	-.20*	-.26***	-.13	-.11***	-.20***	-.14	-.72***
	[-3.53]	[-3.76]	[-1.75]	[-3.40]	[-1.12]	[-3.37]	[-3.20]	[-.65]	[-5.97]
R-squared	.17	.15	.19	.26	.20	.17	.15	.19	--
F-statistics (first-stage)	--	33.59	25.55	15.71	31.05	23.36	23.76	16.50	2.65
Average GDP per capita	$3,708	$3,708	$4,006	$5,018	$4,216	$4,486	$2,950	$2,063	$22,053
Observations	1,264	1,264	627	464	448	928	691	356	626

Notes: T-statistics are in brackets. Each observation is a country-year. 'Northern hemisphere (Northern hemisphere*)' represents the countries with latitude greater than 10 (20). 'Equator' represents the countries whose latitude is between -20 and 20. Each regression includes country and year fixed effects. Robust standard errors are clustered by country. *** p < 0.01, ** p < 0.05, * p < 0.1.

Table 8 Manufacturing Output and Crop Yield, Robustness

	Dependent variable: Manufacturing output, t (in log growth)						
	GDP per capita < $10,000 Northern hemisphere countries						
	Using crop-area weighted rainfall as instrument				Using non-crop area rainfall as instrument		
	baseline (1)	low credit (2)	low trade (3)	agricultural (4)	baseline (5)	low credit (6)	low trade (7)
Log yield growth, t-1	.18** [2.33]	.29*** [3.02]	.31** [2.15]	.25** [2.33]	.20* [1.66]	.27** [2.29]	.26 [1.37]
Log yield growth, t	.02 [.13]	.11 [.72]	.13 [.53]	.04 [.26]	-.05 [-.31]	-.02 [-.14]	.06 [.35]
Log exchange rate growth, t	-.20* [-1.75]	-.32*** [-3.42]	-.40*** [-3.13]	-.36*** [-3.44]	-.19* [-1.66]	-.32*** [-3.39]	-.41*** [-3.26]
R-squared	.19	.22	.27	.26	.15	.19	.27
F-statistics (first-stage)	25.55	38.23	12.65	22.77	17.17	37.86	12.21
average GDP per capita	$4,006	$4,287	$3,472	$3,532	$3,898	$3,412	$3,453
Observations	627	380	376	447	593	346	367

Notes: T-statistics are in brackets. Each observation is a country-year. The sample is restricted to the Northern hemisphere countries whose latitude is greater than 10, and GDP per capita less than $10,000. 'Agricultural' represents observations with shares of agriculture production out of GDP greater than 10%. 'Low trade' represents observations with export shares in manufacturing output less than 20%. 'Low credit' represents observations with private credit (% of total GDP) less than 30%. For regressions (6)-(8), non-crop area weighted rainfall is used as instrument. Each regression includes country and year fixed effects. Robust standard errors are clustered by country. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 9 Employment in Manufacturing and Crop Yield

	Dependent variable: Employment in Manufacturing, t (in log growth rates)								
	GDP per capita < $10,000						GDP per capita < $4,000		GDP per capita > $10,000
	Northern hemisphere				Northern hemisphere*	Equator	Northern hemisphere	Northern hemisphere*	Northern hemisphere
	OLS	baseline IV	Sub-Saharan Africa Excluded	low credit	IV	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log yield growth, t	.04**	.22***	.24***	.29***	.25***	-.10	.29***	.35***	.21
	[2.02]	[3.51]	[3.30]	[5.49]	[3.19]	[-.97]	[4.01]	[2.70]	[.16]
Log yield growth, t-1	.02	-.03	.01	-.02	.01	.01	.01	.14	.97
	[.75]	[-.35]	[.07]	[-.12]	[.07]	[.17]	[.06]	[.79]	[.63]
Log exchange rate growth, t	-.03*	-.03*	-.04*	-.01	-.04*	-.01	-.01	-.02	-.04
	[-1.79]	[-1.71]	[-1.99]	[-.36]	[-1.89]	[-.71]	[-.25]	[-.43]	[-.50]
R-squared	.16	.04	.04	.06	.01	.10	--	--	--
F-statistics (first-stage)	--	34.48	27.85	38.70	43.75	47.53	23.82	26.14	.52
Observations	780	780	735	470	562	802	466	304	628

Notes: T-statistics are in brackets. Each observation is a country-year. 'Northern hemisphere (Northern hemisphere*)' stands for the countries with latitude greater than 10 (20). 'Equator' stands for the countries whose latitude is between -20 and 20. 'Low credit' represents observations with private credit (% of total GDP) less than 30%. Each regression includes country and year fixed effects. Robust standard errors are clustered by country.
*** p < 0.01, ** p < 0.05, * p < 0.1.

Table 10 Sector-level Employment in Manufacturing (instrumented with rainfall)

	Dependent variable: Employment in Manufacturing, t (in log growth rates)							
	Food (Sector 1)	Textiles (Sector 2)	Wood (Sector 3)	Chemicals (Sector 4)	Plastics (Sector 5)	Basic Metals & Equipment (Sector 6)	Electrical Machinery (Sector 7)	Motor Vehicles (Sector 8)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log yield growth, t	.14* [1.79]	.09 [1.10]	.55*** [3.42]	.11 [.80]	.24** [2.57]	.47*** [2.63]	.01 [.04]	-.14 [-.61]
Log yield growth, t-1	.16 [1.23]	-.09 [-.60]	-.09 [-.61]	-.05 [-.35]	.19 [.99]	.15 [.70]	-.13 [-.95]	.25 [.64]
Log exchange rate growth, t	.04 [1.31]	.05 [.88	-.01 [-.26]	-.04 [-.80]	.02 [.44]	.01 [.18]	-.11 [-1.64]	.01 [.20]
R-squared	.19	.10	--	.13	.07	.09	.25	.07
Observations	466	466	466	461	461	448	417	383

Notes: T-statistics are in brackets. Each observation is a country-year. The sample is restricted to the Northern hemisphere countries with GDP per capita less than $4,000. Each regression includes country and year fixed effects. Robust standard errors are clustered by country. *** p < 0.01, ** p < 0.05, * p < 0.1.

Table 11 Capital Investment in Manufacturing and Crop Yield (instrumented with rainfall)

	Dependent variable: Capital investment in Manufacturing, t (in log growth rates)					
	GDP per capita < $10,000			GDP per capita < $4,000	GDP per capita < $15,000	GDP per capita > $15,000
			low trade			
	OLS (1)	IV (2)	IV (3)	IV (4)	IV (5)	IV (6)
Log yield growth, t-1	-.01 [-.13]	1.66** [2.33]	1.56 [1.40]	1.86** [2.33]	1.63** [2.24]	1.01 [.72]
Log yield growth, t	-.10 [-.84]	1.76* [1.79]	5.35** [2.25]	.56 [.60]	1.68 [1.64]	-.78 [-1.26]
Log exchange rate growth, t	-.27*** [-3.62]	-.23*** [-2.67]	-.11 [-.60]	-.40*** [-2.67]	-.22*** [-2.78]	-.1.06*** [-5.70]
F-statistics (first-stage)	--	10.93	3.36	6.03	11.64	.82
Observations	763	763	386	400	865	513

Notes: T-statistics are in brackets. Each observation is a country-year. 'Low trade' represents observations with export shares in manufacturing output less than 20%. Each regression includes country and year fixed effects. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 12 Sector-level Capital Investment in Manufacturing (instrumented with rainfall)

	Dependent variable: Capital Investment in Manufacturing, t (in log growth rates)							
	Food (Sector 1)	Textiles (Sector 2)	Wood (Sector 3)	Chemicals (Sector 4)	Plastics (Sector 5)	Basic Metals & Equipment (Sector 6)	Electrical Machinery (Sector 7)	Motor Vehicles (Sector 8)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log yield growth, t-1	.43	.91	.21	1.00	1.85	2.07*	.17	2.00
	[.74]	[1.19]	[.29]	[1.28]	[1.62]	[1.92]	[.22]	[1.25]
Log yield growth, t	.71	1.35	.35	.63	3.76**	2.06	2.02**	3.80
	[.84]	[1.23]	[.35]	[.56]	[2.33]	[1.41]	[1.99]	[1.26]
Log exchange rate growth, t	-.16**	-.19**	-.19**	-.12	-.31**	-.08	-.19*	-.09
	[-2.25]	[-2.03]	[-2.14]	[-1.31]	[-2.23]	[-.67]	[-1.66]	[-.61]
Observations	758	751	764	741	737	753	660	641

Notes: T-statistics are in brackets. Each observation is a country-year. The sample is restricted with GDP per capita less than $10,000. Each regression includes country and year fixed effects. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 13 Employment Results with 10 Lags of Drought Dummies

	Dependent variable: Employment in Manufacturing, t (in log growth rates)			
	GDP per capita < $10,000 & Northern Hemisphere			
	all	GDP per capita < $4,000	low credit	latitude > 20
	(1)	(2)	(3)	(4)
Drought, t	-.02*** [-2.74]	-.04*** [-2.75]	-.03** [-2.18]	-.02** [-2.06]
Drought, t-1	.05** [2.05]	.07** [2.30]	.07* [1.84]	.04 [1.55]
Drought, t-2	-.00 [-0.29]	.00 [0.07]	.01 [0.35]	-.01 [-0.55]
Drought, t-3	-.01 [-0.68]	-.02 [-1.20]	-.01 [-0.78]	-.00 [-0.06]
Drought, t-4	.01 [0.37]	.01 [0.23]	.01 [0.51]	-.01 [-0.47]
Drought, t-5	-.01 [-0.72]	-.03 [-1.11]	-.01 [-0.49]	-.01 [-0.90]
Drought, t-6	-.00 [-0.03]	.01 [0.42]	.03 [0.86]	.01 [0.29]
Drought, t-7	.02 [1.15]	.02 [0.67]	.03 [1.15]	.03 [1.20]
Drought, t-8	.01 [0.40]	.04** [2.22]	.01 [0.61]	.00 [0.28]
Drought, t-9	.00 [0.28]	.01 [0.31]	.02 [1.10]	.01 [0.59]
Drought, t-10	.00 [0.05]	-.01 [-0.42]	-.01 [-0.22]	.01 [0.25]
Log exchange rate growth, t	.03* [-1.72]	-.01 [-0.38]	-.02 [-0.91]	-.04** [-2.25]
R-squared	.15	.18	.17	.15
Observations	596	344	368	437

Notes: T-statistics are in brackets. Each observation is a country-year. 'Drought, t' represents a dummy variable which takes 1 if the precipitation level at time t is lower than 90% of the average precipitation of the country. 'Low credit' represents observations with private credit (% of total GDP) less than 30%. 'Northern hemisphere' stands for the countries with latitude greater than 10. Each regression includes country and year fixed effects. Robust standard errors are clustered by country. *** p < 0.01, ** p < 0.05, * p < 0.1

Table 14 Employment Results with 10 Lags of Precipitation Levels

	Dependent variable: Employment in Manufacturing, t (in log growth rates)							
	GDP per capita < $10,000 & Northern Hemisphere							
	all		GDP per capita < $4,000		low credit		latitude > 20	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log rainfall, t	.09** [2.42]	.08** [2.30]	.13** [2.42]	.11** [2.27]	.18** [2.32]	.16** [2.21]	.10* [2.04]	.08* [1.80]
Log rainfall, t-1	-.08 [-1.23]	-.07 [-1.14]	-.12 [-1.41]	-.11 [-1.45]	-.13 [-1.07]	-.14 [-1.08]	-.07 [-0.95]	-.06 [-0.85]
Log rainfall, t-2	.02 [0.60]	.01 [0.42]	.02 [0.48]	.01 [0.27]	.04 [0.55]	.01 [0.16]	.03 [0.97]	-.02 [0.70]
Log rainfall, t-3	.01 [0.65]	.01 [0.37]	.01 [0.22]	.01 [0.27]	.01 [0.22]	-.02 [-0.26]	-.00 [-0.02]	-.01 [-0.18]
Log rainfall, t-4		.01 [0.23]		.02 [0.65]		-.04 [-0.98]		.02 [0.79]
Log rainfall, t-5		.04 [1.00]		.07 [1.26]		.05 [0.49]		.04 [1.17]
Log rainfall, t-6		-.04 [-0.78]		-.07 [-1.00]		-.12 [-1.12]		-.06 [-0.72]
Log rainfall, t-7		-.09 [-1.37]		-.11 [-1.17]		-.14 [-1.23]		-.12 [-1.34]
Log rainfall, t-8		.02 [0.45]		-.02 [-0.48]		.05 [0.87]		.02 [0.30]
Log rainfall, t-9		-.01 [-0.27]		-.01 [-0.20]		-.10* [-1.97]		-.03 [-0.57]
Log rainfall, t-10		.01 [0.36]		.01 [0.28]		.02 [0.38]		.02 [0.42]
Log exchange rate growth, t	-.03* [-1.75]	-.03 [-1.45]	-.02 [-0.46]	-.01 [-0.16]	-.02 [-0.74]	-.01 [-0.21]	-.04** [-2.07]	-.04* [-1.96]
R-squared	0.14	0.16	0.16	0.18	0.7	0.21	0.15	0.17
Observations	596	596	344	344	368	368	437	437

Notes: T-statistics are in brackets. Each observation is a country-year. 'Low credit' represents observations with private credit (% of total GDP) less than 30%. 'Northern hemisphere' stands for the countries with latitude greater than 10. Each regression includes country and year fixed effects. Robust standard errors are clustered by country. *** p < 0.01, ** p < 0.05, * p < 0.1

Table 15 Employment Results with Longer Lags of Log Crop Yield Growth (instrumented with rainfall)

	Dependent variable: Employment in Manufacturing, t (in log growth rates)															
	GDP per capita < $10,000 & Northern Hemisphere															
	all				GDP per capita < $4,000				low credit				latitude > 20			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Log yield growth, t	0.22*** [3.25]	.22*** [3.51]	.19** [2.33]	.19* [1.85]	.26*** [4.05]	.29*** [4.01]	.24*** [2.79]	.25** [2.33]	.31*** [4.40]	.29*** [5.49]	.28*** [3.79]	.35*** [3.50]	.26*** [2.93]	.25*** [3.19]	.23** [2.43]	.28** [2.24]
Log yield growth, t-1		-.03 [-0.35]	-.04 [-0.38]	-.07 [-0.64]		.01 [0.06]	-.02 [-0.15]	-.08 [-0.56]		-.02 [-0.12]	.03 [0.22]	.05 [0.32]		0.01 [0.07]	.06 [0.37]	.03 [0.22]
Log yield growth, t-2			-.02 [-0.40]	-.06 [-0.81]			-.06 [-0.67]	-.13 [-0.99]			.06 [0.74]	.06 [0.61]			.06 [0.60]	-.04 [-0.26]
Log yield growth, t-3				-.02 [-0.28]				-0.5 [-0.79]				.11 [1.49]				-.07 [-0.62]
Log exchange rate growth, t	-.03 [-1.34]	-.03* [-1.71]	-.04* [-1.70]	-.05** [-2.08]	.00 [0.03]	-.01 [-0.25]	-.00 [-0.07]	-.01 [-0.27]	-.01 [-0.32]	-.01 [-0.36]	-.00 [-0.09]	-.02 [-0.58]	-.04** [-1.96]	-.04* [-1.89]	-.05** [-2.33]	-.06*** [-3.17]
R-squared	0.03	0.04	0.06	0.03	-	-	0.02	-	0.06	0.06	0.08	0.05	0.00	0.01	0.05	-
Observations	804	780	750	722	483	466	448	429	481	470	451	433	580	562	539	518

Notes: T-statistics are in brackets. Each observation is a country-year. 'Low credit' represents observations with private credit (% of total GDP) less than 30%. 'Northern hemisphere' stands for the countries with latitude greater than 10. Each regression includes country and year fixed effects. Robust standard errors are clustered by country. *** p < 0.01, ** p < 0.05, * p < 0.1

Table 16 Output Results with 10 Lags of Drought Dummies

	Dependent variable: Manufacturing output, t (in log growth rates)				
	GDP per capita < $10,000 & Northern Hemisphere				
	all	GDP per capita < $4,000	low trade	agricultural	latitude > 20
	(1)	(2)	(3)	(4)	(5)
Drought, t	-.02 [-0.66]	-.05** [-2.27]	-.06** [-2.06]	-.06** [-1.99]	-.03 [-0.84]
Drought, t-1	-.01 [-0.47]	-.02 [-0.43]	-.01 [-0.31]	-.01 [-0.32]	-.01 [-0.43]
Drought, t-2	.04* [1.73]	.09*** [3.29]	.07* [1.86]	.05* [1.95]	.05** [2.05]
Drought, t-3	.06* [2.03]	.10*** [3.14]	.04 [1.27]	.04 [1.40]	.06** [2.18]
Drought, t-4	-.00 [-0.14]	.03 [0.71]	.01 [0.40]	-.01 [-0.44]	.03 [1.22]
Drought, t-5	.02 [0.63]	-.00 [-0.12]	-.00 [-0.08]	.02 [0.72]	.02 [0.89]
Drought, t-6	.04 [1.45]	.07 [1.64]	.06* [1.82]	.04 [1.23]	.07 [1.91]
Drought, t-7	.02 [0.86]	-.04 [-1.35]	.04 [1.53]	.00 [0.07]	.03 [1.02]
Drought, t-8	-.00 [-0.04]	.00 [0.09]	.02 [0.73]	.03 [1.61]	.02 [0.94]
Drought, t-9	-.01 [-0.33]	-.01 [-0.27]	-.01 [-0.24]	-.01 [-0.24]	.01 [0.35]
Drought, t-10	.01 [0.24]	.04 [0.90]	-.01 [-0.20]	-.01 [-0.31]	.02 [0.64]
Log exchange rate growth, t	-.17 [-1.60]	-.10 [-0.52]	-.35*** [-2.75]	-.35*** [-3.66]	-.12 [-1.01]
R-squared	0.23	0.32	0.36	0.30	0.24
Observations	469	259	272	361	346

Notes: T-statistics are in brackets. Each observation is a country-year. 'Drought, t' represents a dummy variable which takes 1 if the precipitation level at time t is lower than 90% of the average precipitation of the country. 'Low trade' represents observations with export shares in manufacturing output less than 20%. 'Agricultural' represents observations with shares of agriculture production out of GDP greater than 10%. 'Northern hemisphere' stands for the countries with latitude greater than 10. Each regression includes country and year fixed effects. Robust standard errors are clustered by country. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 17 Output Results with 10 Lags of Precipitation Levels

	Dependent variable: Manufacturing output, t (in log growth rates)							
	GDP per capita < $10,000 & Northern Hemisphere							
	all		GDP per capita < $4,000		low trade		low credit	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log rainfall, t	-.04 [-0.57]	-.05 [-0.60]	-.04 [-0.31]	-.03 [-0.22]	.02 [0.18]	-.02 [-0.21]	-.04 [-0.28]	-.06 [-0.41]
Log rainfall, t-1	-.03 [-0.55]	-.03 [-0.73]	-.02 [-0.27]	-.03 [-0.38]	-.05 [-0.91]	-.05 [-0.75]	-.02 [-0.22]	-.03 [-0.35]
Log rainfall, t-2	-.13** [-2.24]	-.14** [-2.33]	-.18* [-1.95]	-.19* [-1.86]	-.21** [-2.51]	-.24** [2.71]	-.27* [-1.81]	-.28* [-1.94]
Log rainfall, t-3	-.05 [-0.79]	-.04 [-.59]	-.02 [-0.25]	.00 [0.00]	-.15** [-2.08]	-.11 [-1.45]	-.07 [-0.96]	-.09 [-1.16]
Log rainfall, t-4		-0.01 [-0.23]		-.09 [-0.93]		-.07 [-0.74]		-.02 [-0.23]
Log rainfall, t-5		0.01 [0.18]		.05 [0.57]		.11 [0.99]		0.12 [1.10]
Log rainfall, t-6		-.04 [-0.50]		-.06 [-.44]		-.06 [-0.51]		-.19 [-1.45]
Log rainfall, t-7		0.00 [0.04]		.05 [0.59]		-.07 [-1.07]		-.05 [-0.55]
Log rainfall, t-8		-.04 [-0.89]		-.12* [-1.82]		-.08 [-0.67]		-.07 [-0.62]
Log rainfall, t-9		-.06 [-0.76]		0.00 [0.02]		.08 [-0.79]		-.14 [-0.96]
Log rainfall, t-10		.01 [0.26]		.02 [0.43]		.05 [0.61]		.01 [0.15]
Log exchange rate growth, t	-.18* [-1.49]	-.18 [-1.48]	-.11 [-0.48]	-.11 [-0.47]	-.38*** [-2.78]	-.37** [-2.52]	-.30*** [-2.63]	-.29** [-2.74]
R-squared	0.22	0.23	0.29	0.26	0.36	0.37	0.23	0.25
Observations	469	469	259	259	272	272	281	281

Notes: T-statistics are in brackets. Each observation is a country-year. 'Low trade' represents observations with export shares in manufacturing output less than 20%. 'Northern hemisphere' stands for the countries with latitude greater than 10. Each regression includes country and year fixed effects. Robust standard errors are clustered by country. *** p < 0.01, ** p < 0.05, * p < 0.1

Table 18 Output Results with Longer Lags of Log Crop Yield Growth (instrumented with rainfall)

	Dependent variable: Manufacturing output, t (in log growth rates)													
	GDP per capita < $10,000 & Northern Hemisphere													
	agricultural				low trade				low credit			latitude > 20		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Log yield growth, t		.04 [0.26]	.01 [0.08]	.06 [0.33]		.13 [0.53]	.06 [0.22]	-.08 [-0.22]		.11 [0.72]	.11 [0.54]	.15 [0.65]	.22 [0.85]	.25 [0.57]
Log yield growth, t-1	.24** [2.15]	.25** [2.33]	.24** [2.07]	.26** [2.32]	.27* [1.95]	.31** [2.15]	.36** [1.97]	.33* [1.73]	.25** [2.06]	.29*** [3.02]	.28** [2.53]	.26** [2.24]	.42* [1.84]	.41* [1.67]
Log yield growth, t-2			-.04 [-0.36]	-.02 [-0.18]			.12 [0.98]	.03 [0.15]			.01 [0.07]		.18 [1.22]	.01 [0.03]
Log yield growth, t-3				.02 [0.18]				-.17 [-0.77]						-.22 [-1.00]
Log exchange rate growth, t	-.36*** [-3.38]	-.36*** [-3.44]	-.35*** [-3.29]	-.35*** [-3.39]	-.42*** [-3.54]	-.40*** [-3.13]	-.41*** [-3.20]	-.43*** [-3.23]	-.32*** [-3.47]	-.32*** [-3.42]	-.31*** [-3.29]	-.13 [-1.12]	-.12 [-0.98]	-.12 [-0.95]
R-squared	0.26	0.26	0.26	0.26	0.25	0.27	0.24	0.18	0.21	0.22	0.22	0.21	0.16	0.10
Observations	447	447	434	423	376	376	376	362	380	380	365	448	433	419

Notes: T-statistics are in brackets.
Each observation is a country-year. 'Low trade' represents observations with export shares in manufacturing output less than 20%. 'Northern hemisphere' stands for the countries with latitude greater than 10. Each regression includes country and year fixed effects. Robust standard errors are clustered by country. *** p < 0.01, ** p < 0.05, * p < 0.1

Appendices

A Equilibrium Solution Derivations

A.1 Baseline model

A representative agent has a Cobb-Douglas Stone-Geary utility function:

$$U = (q_a - \gamma_a)^{\alpha} q_m^{1-\alpha}, \qquad 0 < \alpha < 1,$$

Solving the utility maximization problem subject to the budget constraint, $p_a q_a + q_m = I$, yields the following expenditure equation for manufacturing:

$$E_m = (1-\alpha)(I - p_a \gamma_a)$$

On the production side, recall that, given prices, each sector chooses K_i and L_i to maximize profits,

$$\pi_i = p_i f_i(K_i, L_i) - wL_i - rK_i,$$

where $i = a, m$. First order conditions are then given by,

$$w = (1-\beta_m) z_m (\frac{K_m}{L_m})^{\beta_m} = p_a (1-\beta_a) z_a (\frac{K_a}{L_a})^{\beta_a} \tag{A.1}$$

$$r = \beta_m z_m (\frac{K_m}{L_m})^{\beta_m - 1} = p_a \beta_a z_a (\frac{K_a}{L_a})^{\beta_a - 1} \tag{A.2}$$

Using Equations (A.1) and (A.2), both p_a and K_m can be expressed in terms of L_m as follows:

$$K_m = \frac{\beta_m (1-\beta_a) L_m K}{\beta_a (1-\beta_m) L + (\beta_m - \beta_a) L_m} \tag{A.3}$$

$$\begin{aligned} p_a &= \tfrac{z_m \beta_m}{z_a \beta_a} (\tfrac{K_m}{L_m})^{\beta_m - 1} (\tfrac{L - L_m}{K - K_m})^{\beta_a - 1} \\ &= \tfrac{z_m \beta_m}{z_a \beta_a} [\tfrac{\beta_a (1-\beta_m) L + (\beta_m - \beta_a) L_m}{K}]^{\beta_a - \beta_m} [\beta_m (1-\beta_a)]^{\beta_m - 1} [\beta_a (1-\beta_m)]^{1-\beta_a} \end{aligned} \tag{A.4}$$

Using the market clearing condition and Equations (A.1) - (A.4), I obtain the following:

$$\begin{aligned} z_m K_m^{\beta_m} L_m^{1-\beta_m} &= (1-\alpha)(wL + rK - p_a \gamma_a) \\ &= (1-\alpha)[(1-\beta_m) z_m (\tfrac{K_m}{L_m})^{\beta_m} L + \beta_m z_m (\tfrac{K_m}{L_m})^{\beta_m - 1} K \\ &- \tfrac{z_m \beta_m}{z_a \beta_a} (\tfrac{K_m}{L_m})^{\beta_m - 1} (\tfrac{L - L_m}{K - K_m})^{\beta_a - 1} \gamma_a] \end{aligned} \tag{A.5}$$

Substituting Equation (A.3) for K_m in Equation (A.5), I obtain the following implicit solution for L_m,

$$\frac{1}{z_a} \cdot \frac{\gamma_a}{K^{\beta_a}} = G(L_m), \tag{A.6}$$

where $G(L_m) = \frac{L-\lambda^{-1}\cdot L_m}{[L+\frac{(\beta_m-\beta_a)}{\beta_a(1-\beta_m)}L_m]^{\beta_a}}$ and $\lambda = \frac{(1-\alpha)(1-\beta_m)}{(1-\alpha)(1-\beta_m)+\alpha(1-\beta_a)}$. Other remaining equilibrium allocations can be easily obtained from knowing the equilibrium value L_m^*.[1]

In order to illustrate the intuition about the model, Figure A.1 presents how equilibrium output changes in response to a decrease in agricultural productivity using production possibility frontiers (PPF) and Stone-Geary utility indifference curves. The y-axis and x-axis represent the amounts of agricultural and manufacturing goods, respectively. The outer PPF shrinks vertically to the inner one in response to a negative shock to agricultural productivity. The top two Stone-Geary indifference curves have a high level of subsistence requirement, while the two lower indifference curves have a low subsistence requirement. Equilibrium output occurs at points where the indifference curves and PPFs are tangent. The equilibrium manufacturing output that is associated with the higher level of subsistence falls from M1 to M2 in response to a decrease in agricultural productivity. Meanwhile, the one with the lower level of subsistence decreases from m1 to m2. From the figure, it can be noted that $M1/M2 > m1/m2$. The change in equilibrium in response to a shock to agricultural productivity is largest when the country is producing mostly agricultural goods (near the y-axis), and when the country's income is close to the subsistence level (Implication 2).

How does the result differ if one assumes the subsistence requirement γ_a to be zero? The utility function then becomes the Cobb-Douglas utility function, and a new general equilibrium solution for L_m can be obtained using Equation (7) as follows:

$$L_m = \lambda \cdot L = \frac{(1-\alpha)(1-\beta_m)}{(1-\alpha)(1-\beta_m)+\alpha(1-\beta_a)}L \tag{A.7}$$

Note that consumers pay $(1-\alpha)\cdot I$ for manufacturing, and the Cobb-Douglas production technology implies that fraction $(1-\beta_m)$ of $(1-\alpha)\cdot I$ is spent on labor in manufacturing. Similarly, fraction $(1-\beta_a)$ of $\alpha \cdot I$ is spent on labor in agriculture. Thus, Equation (A.7) implies that the manufacturing employment share equals the portion of spending for manufacturing employment out of spending on total employment.[2] Unlike the case with Stone-Geary preferences, note that Equation (A.7) does not involve productivity terms z_a and z_m. This implies that agricultural productivity does not affect manufacturing output under the assumption of Cobb-Douglas preferences.

A.2 Extension: CES preferences

Consider a more generalized case with a CES Stone-Geary preference,

$$U = [\alpha(q_a-\gamma_a)^{(\sigma-1)/\sigma} + (1-\alpha)q_m^{(\sigma-1)/\sigma}]^{\sigma/(\sigma-1)}$$

[1] $L_a^* = L - L_m^*; K_m^* = \frac{\beta_m(1-\beta_a)L_m^*K}{\beta_a(1-\beta_m)L+(\beta_m-\beta_a)L_m^*}; K_A^* = K - K_m^*; p_a^* = \frac{z_m\beta_m}{z_a\beta_a}(\frac{K_m^*}{L_m^*})^{\beta_m-1}(\frac{L-L_m^*}{K-K_m^*})^{\beta_a-1}$

$q_m^* = z_m {K_m^*}^{\beta_m} {L_m^*}^{\beta_m-1}; q_a^* = z_a {K_a^*}^{\beta_a} {L_a^*}^{\beta_a-1}$

[2] Similarly, the equilibrium allocation for capital in manufacturing is,

$$K_m = \frac{(1-\alpha)\beta_m}{\alpha\beta_a+(1-\alpha)\beta_m}K$$

Solving the utility maximization problem subject to the budget constraint $p_a q_a + q_m = I$ yields the following manufacturing expenditure equation:

$$E_m = \widehat{\alpha_m}(\sigma, p_a) \cdot (I - p_a \gamma_a),$$

where $\widehat{\alpha_m}(\sigma, p_a) = \frac{(1-\alpha)^\sigma}{\alpha^\sigma p_a^{1-\sigma} + (1-\alpha)^\sigma}$. $\widehat{\alpha_m}(\sigma, p_a)$ indicates the share of residual income spent on manufacturing, and $\widehat{\alpha_m}(\sigma, p_a) \to (1-\alpha)$, as $\sigma \to 1$.

The market clearing condition and Equations (A.1) - (A.4) yields the following:

$$\begin{aligned} z_m K_m^{\beta_m} L_m^{1-\beta_m} &= \widehat{\alpha_m}(\sigma, p_a)(wL + rK - p_a \gamma_a) \\ &= \widehat{\alpha_m}(\sigma, p_a)[(1-\beta_m) z_m (\tfrac{K_m}{L_m})^{\beta_m} L + \beta_m z_m (\tfrac{K_m}{L_m})^{\beta_m - 1} K \qquad \text{(A.8)} \\ &- \tfrac{z_m \beta_m}{z_a \beta_a} (\tfrac{K_m}{L_m})^{\beta_m - 1} (\tfrac{L - L_m}{K - K_m})^{\beta_a - 1} \gamma_a] \end{aligned}$$

By substituting Equation (A.3) and (A.4) for K_m and p_a in Equation (A.8), I obtain the following implicit solution for L_m:

$$\frac{1}{z_a} \cdot \frac{\gamma_a}{K^{\beta_a}} = \tilde{G}(L_m) \qquad \text{(A.9)}$$

, where $\tilde{G}(L_m) = \frac{L - \lambda_2(p_a)^{-1} \cdot L_m}{[L + \frac{(\beta_m - \beta_a)}{\beta_a(1-\beta_m)} L_m]^{\beta_a}}$; $\lambda_2(p_a(L_m)) = \frac{\widehat{\alpha_m}(\sigma,p_a)(1-\beta_m)}{\widehat{\alpha_m}(\sigma,p_a)(1-\beta_m) + \widehat{\alpha_a}(\sigma,p_a)(1-\beta_a)}$

; $p_a(L_m) = \frac{z_m \beta_m}{z_a \beta_a} [\frac{\beta_a(1-\beta_m)L + (\beta_m - \beta_a)L_m}{K}]^{\beta_a - \beta_m} [\beta_m(1-\beta_a)]^{\beta_m - 1} [\beta_a(1-\beta_m)]^{1-\beta_a}$.

In order to clearly see how the substitution effect with $\sigma > 1$ can change the volatility pattern, I increase the value of α to 0.5, and generate new simulation results. Figure A.1 plots the elasticity of manufacturing output with respect to agricultural productivity against the residual income $I - p_a \gamma_a$ as a percentage of total income.[3] Consistent with the analysis, the elasticity curve for the CES model is placed lower than the one for the baseline model, and both elasticities are decreasing with income levels due to declining income effects. Note that the elasticity of the CES model hits zero when the residual income share is about 28%. This point is where the positive sign income effect equals the negative sign substitution effect. After passing this point, the substitution effect dominates, thus the sign of the elasticity becomes negative.

Figure A.2 displays manufacturing output volatility against income levels, and it shows that the volatility pattern is U-shaped for the CES case.[4] Note that the level of volatility is zero when the share of residual income is about 28%, the point at which the elasticity becomes zero in Figure A.1. For the range where the residual income share is less than 28%, the level of volatility decreases with income levels as the elasticity decreases. When

[3]For the simulation, I set $z_a = 1$, and $K = 1$. The elasticities are calculated as percentage change in manufacturing output in response to a 1% increase in z_a. In order to have target residual income, I vary γ_a.

[4]In order to plot the volatility curves, I randomly draw z_a 33 times from a truncated normal distribution $N_{[0.99,1.01]}(1, 0.0001)$. I then simulate equilibrium solutions and calculate the standard deviation of output growth rates.

the residual income share is greater than 28%, the volatility starts increasing because the absolute value of elasticity – although the sign is negative – starts increasing.

A.3 Two-country model

Consider a world economy consisting of two countries of the baseline model type, indexed by $c = H, F$. The two countries produce homogenous manufacturing and agricultural goods, and engage in free trade with no transportation costs. The countries have the following aggregate preferences:

$$U_H = (q_{a,H} - L_H\gamma_a)^{\alpha} q_{m,H}^{1-\alpha} \tag{A.10}$$

$$U_F = (q_{a,F} - L_F\gamma_a)^{\alpha} q_{m,F}^{1-\alpha} \ . \tag{A.11}$$

Each country's group of agents maximizes their utility subject to the budget constraint $I_c = p_a q_{a,c} + q_{m,c}$. The production side of each country takes the same Cobb-Douglas production technology as in the baseline model.

Using the fact that there will be the same relative price p_a in both Home and Foreign countries and Equation (A.4), which is solved for p_a in terms of L_m, I can express $L_{m,F}$ in terms of $L_{m,H}$ as follows:

$$L_{m,F} = \{(\frac{z_{a,F}z_{m,H}}{z_{m,F}z_{a,H}})^{\frac{1}{\beta_a-\beta_m}}[\frac{\beta_a(1-\beta_m)L_H + (\beta_m-\beta_a)L_{m,H}}{K_H}]K_F - \beta_a(1-\beta_m)L_F\} \cdot \frac{1}{\beta_m-\beta_a} \tag{A.12}$$

I also use the market clearing condition for the world market. That is, for each sector, the sum of quantity produced in the world equals the sum of global demand, which yields the following:

$$z_{m,H}K_{m,H}^{\beta_m}L_{m,H}^{1-\beta_m} + z_{m,F}K_{m,F}^{\beta_m}L_{m,F}^{1-\beta_m} = (1-\alpha)[(wL_H + rK_H - p_aL_H\gamma_a) + (wL_F + rK_F - p_aL_F\gamma_a)] \ . \tag{A.13}$$

Plugging (A.1) - (A.4) and (A.12) into (A.13) will yield an implicit solution for $L_{m,H}$.

Small open economy — Now I assume a small open economy where the price is fixed at the world price, $p_a = p_w$. Since the price is fixed, the demand system has no effect on output, so the resource allocations and manufacturing output are entirely determined by the supply side. Thus, I consider only the production side to obtain equilibrium solutions of interest. First order conditions of the production side are,

$$w = (1-\beta_m)z_m(\frac{K_m}{L_m})^{\beta_m} = p_w(1-\beta_a)z_a(\frac{K_a}{L_a})^{\beta_a} \tag{A.14}$$

$$r = \beta_m z_m(\frac{K_m}{L_m})^{\beta_m-1} = p_w\beta_a z_a(\frac{K_a}{L_a})^{\beta_a-1} \tag{A.15}$$

We can solve for p_w using Equation (A.15),

$$p_w = \frac{z_m\beta_m}{z_a\beta_a}(\frac{K_m}{L_m})^{\beta_m-1}(\frac{L-L_m}{K-K_m})^{\beta_a-1} \tag{A.16}$$

Plugging (A.3) into (A.16) to replace K_m with a function of L_m yields:

$$p_w = \frac{z_m \beta_m}{z_a \beta_a}[\frac{\beta_a(1-\beta_m)L + (\beta_m - \beta_a)L_m}{K}]^{\beta_a - \beta_m}[\beta_m(1-\beta_a)]^{\beta_m - 1}[\beta_a(1-\beta_m)]^{\beta_a - 1} \quad (A.17)$$

By rearranging the terms, I obtain the closed form solution for L_m,

$$L_m = (\frac{z_m}{z_a} \cdot \frac{\lambda_3}{p_w})^{\frac{1}{\beta_m - \beta_a}} \cdot \frac{K}{\beta_m - \beta_a} - \frac{\beta_a(1-\beta_m)}{\beta_m - \beta_a} \cdot L \quad (A.18)$$

B Implications for Aggregate TFP

The baseline model predicts that some labor and capital resources move away from manufacturing and into agriculture in response to a negative shock to agricultural productivity. This implication is somewhat counterintuitive, as resources are moving toward the sector with declining productivity. How would such a reallocation pattern affect aggregate TFP? Meanwhile, it has been seen that under the small open economy the direction of resource flow is the opposite, which will affect aggregate productivity differently. This section investigates how the varying patterns of resource reallocations affect aggregate productivity.

Using the same simulation setting which was used to investigate manufacturing output growth rates in response to a -15% productivity shock (see Table A.6), I obtain growth rates in equilibrium aggregate productivity under the two cases: the baseline model and the small open economy model (see columns 3 and 6 of Table A.6). In both cases, the base price is country specific and is set at the equilibrium price obtained in the baseline model setting at time 0 (i.e., before the -15% shock). As for the world price (the agricultural price relative to the manufacturing price in the world) for the small open economy, I assume that the world relative price is country specific rather than common to all countries, due to different consumption baskets across countries (for example, the quality and price of manufacturing goods that are consumed are higher in rich countries). Thus, the world price each country faces is set at the same base price which is the equilibrium price obtained under the baseline model setting at time 0. Note that the primary purpose of setting the world price in this way is to make aggregate output in the two cases comparable. For example, we will see that productivity effects (or, within-sector effecst) are the same in the baseline model and in the small open economy.

The simulation results then show that in response to the 15% decrease in agricultural productivity, there is much less reduction in aggregate TFP in the small open economy.[5] For example, in Ethiopia, aggregate TFP decreases by 13.5% in the closed economy, while it decreases only by 7.6% in the small open economy. How does the same 15% decrease in agricultural productivity result in a larger reduction in aggregate productivity in the closed economy? To investigate this, I decompose the aggregate TFP growth into the productivity effect (within-sector effect) resulting from declining agricultural productivity, and the share

[5]Since I use static models where total capital stock and labor are fixed, the aggregate TFP growth rate is equal to the aggregate output growth rate.

effect (between-sector effect) which operates by reallocating resources.[6]

Decompositions of aggregate TFP growth — Consider a Cobb-Douglas production function for aggregate output with aggregate total factor productivity z,

$$Y = z \cdot K^{\beta} L^{1-\beta} \tag{B.1}$$

Next, aggregate output can be written as the sum of each sector's output,

$$Y = \sum_i Y_i \ , \qquad i = a, m \tag{B.2}$$

By dividing Equation (B.2) by $K^{\beta} L^{1-\beta}$, I can express the aggregate TFP as the weighted sum of sector-specific TFPs as follows:

$$z = \sum_i \underbrace{\frac{Y_i}{K_i^{\beta_i} L_i^{1-\beta_i}}}_{z_i} \cdot \underbrace{(\frac{K_i^{\beta_i} L_i^{1-\beta_i}}{K^{\beta} L^{1-\beta}})}_{S_i} = \sum_i z_i \cdot S_i \quad , \tag{B.3}$$

where the weight S_i is the ratio of the sector i input combination to the aggregate input combination, which I will interpret as sector share.

Using Equation (B.3), we can decompose the change in aggregate TFP into within- and between-sector effects as follows,

$$(z_t - z_{t-1}) = \sum_i (z_{i,t} - z_{i,t-1}) \cdot S_{i,t-1} + \sum_i (S_{i,t} - S_{i,t-1}) \cdot z_{i,t} \tag{B.4}$$

Although there are other ways to decompose the change in TFP, I choose this way since it fits well in the theoretical context. Equation (B.4) can be thought of as the change of aggregate TFP through the following two steps as an example. Imagine a drought that lowers agricultural productivity. First, sector-specific productivity changes from $z_{i,t-1}$ to $z_{i,t}$ (in this case, manufacturing productivity stays the same), while labor and capital resources have not yet been reallocated, so initial sector shares are fixed at $S_{i,t-1}$. Second, having seen the realized productivity $z_{i,t}$, resources move between the sectors and sector shares adjust from $S_{i,t-1}$ to $S_{i,t}$.

Next, I divide Equation (B.4) by z_{t-1}, to rewrite it in terms of percentage changes,

$$\%\Delta z = \underbrace{\sum_i \Delta z_i (\frac{S_{i,t-1}}{z_{t-1}})}_{\text{Productivity effect}} + \underbrace{\sum_i \Delta S_i (\frac{z_{i,t}}{z_{t-1}})}_{\text{Share effect}} \tag{B.5}$$

The first term, the productivity effect, shows the contribution of sector-specific TFP changes to aggregate TFP growth. Sectors either with large changes in their productivity or with

[6] I follow the TFP growth decomposition method introduced by Bernard and Jones (1996) but slightly modified to fit the context of this paper.

large sector shares will have larger productivity effects. The second component, the share effect, captures the indirect effect on the aggregate TFP growth that operates by reallocating resources.

Table A.6 reports the decompositions of aggregate TFP growth in response to a 15% decrease in agricultural productivity. There are two dimensions to compare these results: comparison between closed and open economies, and comparison across countries. Recall that under the closed economy labor and capital resources move toward agriculture when its productivity is declining. Such pattern of resource reallocation negatively contributes to aggregate TFP growth, so the share effects are negative (column 3 of Table A.6). For example, in Ethiopia, the share effect is -2.2% in the closed economy. On the other hand, the share effect in the small open economy is +3.8% (column 6). In short, the country could have done better by more than 6%, if it had been able to freely allocate resources toward the sector that became relatively more productive.

The theory under the closed economy also implies that the effect of agricultural productivity on resource reallocations decreases as the subsistence requirement relative to income decreases. This is reflected by the decreasing share effect (column 3 of Table A.6). Productivity effects are the same in both closed and small open economies (columns 1 and 4). Meanwhile, across countries the productivity effect decreases with income levels due to the decreasing share of agriculture in the economy.

C A Model with Land and Intermediate Inputs in Agriculture

Recall that the agricultural production function in the baseline model had only labor and capital inputs. This section studies a new model that considers land and an intermediate input, which is supplied by the manufacturing sector, in agricultural production. To simplify the algebra, I assume that only labor is used in manufacturing. The demand-side setup and all other assumptions are the same as in the baseline model. Note that this model setup closely resembles the one used by Restuccia, Yang, and Zhu (2008).

Production Technologies — The agricultural production function is assumed as follows:

$$Y_a = f_a(L_a, X) = z_a X^{\beta_1} (Z^{1-\beta_2} L_a^{\beta_2})^{1-\beta_1} \tag{C.1}$$

where Z and X are land and the intermediate input from manufacturing. I assume that the land supply is fixed, so labor in agriculture exhibits decreasing returns. The production function for manufacturing is

$$Y_m = z_m L_m \tag{C.2}$$

Following Restuccia et al.(2008), I assume that p_x units of manufacturing good are needed to produce 1 unit of X, where p_x is given outside the model. Since the manufacturing is treated as the numeraire, p_x can be considered as the price of intermediate inputs. Also, I assume that $w_a = w_m$ to make the model comparable with the baseline model. In addition,

$L_a + L_m = L$ and $Y_m = q_m + X$. Note that profit maximization of the manufacturing sector requires $w = z_m$. The agricultural sector choses L_a and X to maximize the profit

$$\pi_a = p_a z_a X^{\beta_1}(Z^{1-\beta_2}L_a^{\beta_2})^{1-\beta_1} - wL_a - p_x X \tag{C.3}$$

This yields the following first-order conditions:

$$p_a(1-\beta_1)\beta_2 z_a X^{\beta_1} Z^{(1-\beta_2)(1-\beta_1)} L_a^{\beta_2(1-\beta_1)-1} - w = 0 \tag{C.4}$$

$$\beta_1 p_a z_a X^{\beta_1 - 1}(Z^{1-\beta_2}L_a^{\beta_2})^{1-\beta_1} - p_x = 0 \tag{C.5}$$

Preferences — The demand-side is the same as the baseline model. A representative agent has a Cobb-Douglas Stone-Geary utility function:

$$U = (q_a - \gamma_a)^{\alpha} q_m^{1-\alpha}, \qquad 0 < \alpha < 1, \tag{C.6}$$

where γ_a is a subsistence requirement for agricultural goods. The agent earns income $I = wL = z_m L$ by inelastically supplying L units of labor, and the budget constraint is given by:

$$p_a q_a + q_m = I. \tag{C.7}$$

Solving the utility maximization problem of the representative agent subject to the budget constraint yields expenditure equations for food and manufacturing as follows:

$$E_a = \alpha(I - p_a\gamma_a) + p_a\gamma_a \tag{C.8}$$

$$E_m = (1-\alpha)(I - p_a\gamma_a) \tag{C.9}$$

Competitive equilibrium — The competitive equilibrium of the closed economy is a set of allocations $\{L_a, L_m, q_a, q_m, X\}$ and prices $\{w, r, p_a\}$, such that, given the prices, (1) $\{q_a, q_m\}$ solve the utility maximization problem of the representative agent, (2) $\{L_a, L_m, X\}$ solve the profit maximization problem of each sector, and (3) all markets clear. Each equilibrium allocation can then be expressed by the eight parameters, $K, L, Z, p_x, z_a, z_m, \beta_a, \beta_M, \alpha$, and γ_a. Using (C.4) and (C.5), we can express p_a and X in terms of L_a and other parameters as follows:

$$p_a = \left(\frac{z_m}{z_a(1-\beta_1)\beta_2}\right)^{1-\beta_1}\left(\frac{p_x}{z_a\beta_1}\right)^{\beta_1}\left(\frac{L_a}{Z}\right)^{(1-\beta_1)(1-\beta_2)} \tag{C.10}$$

$$X = \frac{z_m\beta_1}{\beta_2(1-\beta_1)p_x}L_a \tag{C.11}$$

Combining (C.9) and the market clearing condition yields:

$$\alpha I + (1-\alpha)p_a\gamma_a = p_a f_a(L_a, X) = p_a z_a X^{\beta_1}(Z^{1-\beta_2}L_a^{\beta_2})^{1-\beta_1} \tag{C.12}$$

Plugging (C.10) and (C.11) into (C.12) leads to an implicit solution of L_a,

$$\alpha z_m L - \left(\frac{z_m}{z_a(1-\beta_1)\beta_2}\right)^{1-\beta_1}\left(\frac{p_x}{z_a\beta_1}\right)^{\beta_1}\left(\frac{L_a}{Z}\right)^{(1-\beta_1)(1-\beta_2)}\left\{z_a\left(\frac{z_m\beta_1 L_a}{\beta_2(1-\beta_1)p_x}\right)^{\beta_1}(Z^{1-\beta_2}L_a^{\beta_2})^{1-\beta_1} - (1-\alpha)\gamma_a\right\} = 0 \tag{C.13}$$

Quantitative analysis — Following Restuccia et al. (2008), the labor income share in agriculture β_2 is set at 0.7. Also, the authors selected $\beta_1 = 0.4$ to match the intermediate input to output ratio for the U.S. economy, and I follow this. In addition, I assume $p_x = 1$ and $Z = 1$. For all other remaining parameters, I use the same values used for the baseline model simulations as listed in Table 1.

With the given parameters, I simulate the new model equilibrium outcome, and find that the key implications of this model are unchanged compared to the baseline model results. That is, when there is a decrease in agricultural productivity, resources move toward agriculture and out of manufacturing, reducing manufacturing output. This effect decreases with income levels, thus output fluctuations are higher in poor countries. Importantly, like the baseline model results, the new model results show that significant differences exist in manufacturing output growth rates across poor and rich countries. For example, Ghana and India experience 19% and 9% decrease in manufacturing output, respectively, while the U.S. experiences only a 1% decrease in manufacturing output.

Appendix Figures and Tables

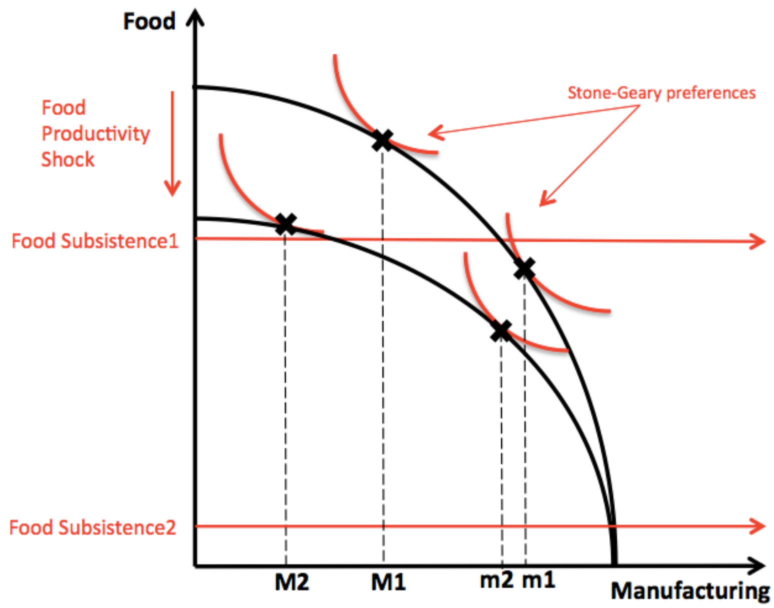

Figure A.1 Changes in equilibrium quantities in response to a negative shock to agricultural productivity

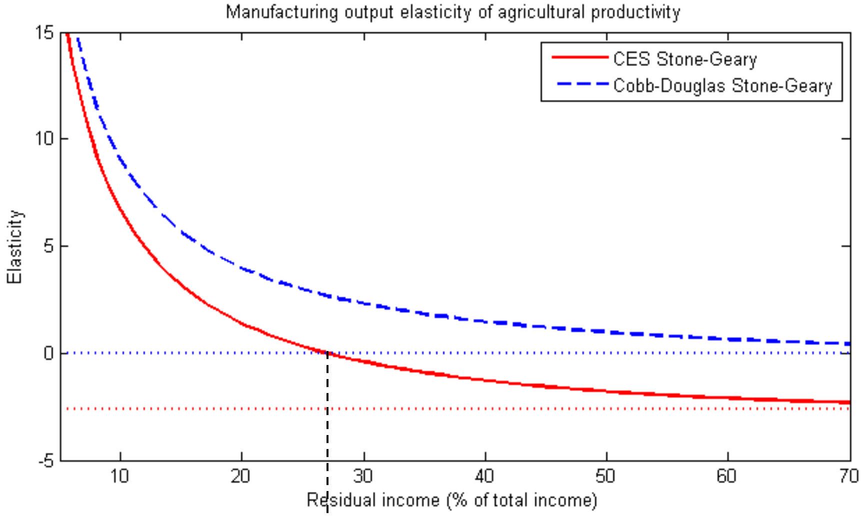

Figure A.2. Elasticity of manufacturing output with respect to agricultural productivity, against residual income (% of total income)

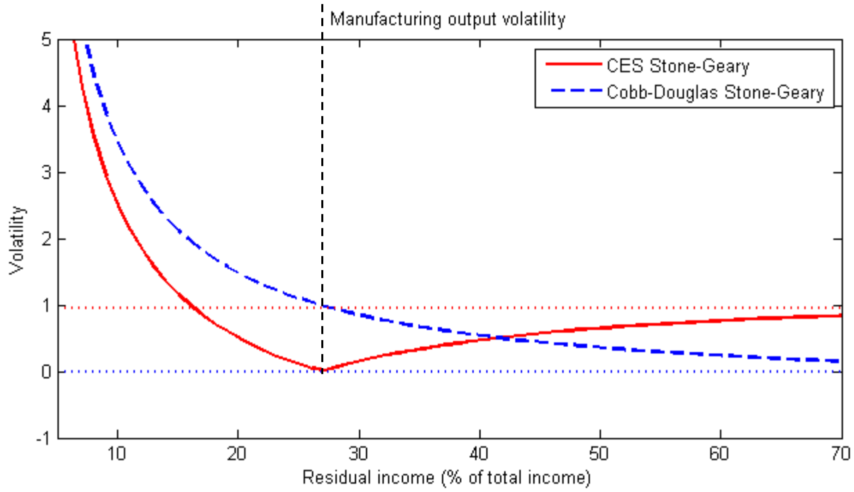

Figure A.3. Manufacturing output volatility against residual income (% of total income)

Table A.1. The negative relationship between volatilities and per capita GDP

	Dependent variables	
	Manufacturing output volatility	Aggregate output volatility
Log PGDP	-.030** [-2.80]	-.007*** [-3.11]
Log population	-.007 [.76]	-.005*** [-2.69]
Constant	.503*** [3.85]	.16*** [5.56]
R-squared	0.095	0.168
Observations	80	80

Note - OLS estimation results. Standard errors are in parentheses. The standard deviations of manufacturing output growth rates and per capita GDP growth rates over the time period 1970-2002 are used as dependent variables. The explanatory variable Log PGDP is the average value of per capita GDP over the period in log. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.2. List of sectors

1	Food and beverages; Tobacco
2	Textiles; Wearing apparel, fur; Leather, leather products and foot wear
3	Wood products (excl. furniture); Paper and paper products; Printing and publishing; Furniture, manufacturing n.e.c. ; Recycling
4	Coke, refined petroleum products, nuclear fuel; Chemicals and chemical products;
5	Rubber and plastics products; Non-metallic mineral products
6	Basic metals; Fabricated metal products; Machinery and equipment n.e.c.; Office, accounting and computing machinery
7	Electrical machinery and apparatus; Radio, television and communication equipment; Medical, precision and optical instruments
8	Motor vehicles, trailers, semi-trailers; Other transport equipment

Table A.3. Standard deviations of the predicted manufacturing output growth rates

Countries	Predicted Volatility 1 (%) (projections of rainfall onto yields) (1)	Predicted Volatility 2 (%) (endogenous variable, yields) (2)	(Data) Volatility (%) (3)	Ratio1 col1/col3 (%) (4)	Ratio2 col2/col3 (%) (5)
Burkina Faso	3.9	4.5	11.7	33.1	38.3
Bangladesh	6.9	7.1	25.1	27.6	28.5
India	5.7	5.8	10.2	56.3	57.3
Morocco	6.3	13.9	19.1	33.0	72.7
Egypt, Arab Rep.	6.8	6.2	20.5	33.0	30.2
Philippines	6.0	6.3	16.9	35.4	37.0
Algeria	6.0	7.0	18.7	32.0	37.3
Sample Average	5.4	7.1	22.8	31.3	44.0

Notes: Volatility in percentage terms can be understood simply as the standard deviation of growth rates in percentage. Column 1 presents predicted volatility using projections of rainfall onto yields, while column 2 uses the endogenous variable itself, crop yield data. Volatility values in column 3 are computed directly from the data over the same sample. Column 4 (5) values are obtained from column 1 (2) values divided by column 3 values. The last row displays the mean values across the sample countries.

Table A.4 Domestic Productivity Shocks and Crop Prices (instrumented with rainfall)

	Dependent variables (in log growth rates)						
	Wheat price	Wheat price	Maize price	Barley price	Soybean price	Sorghum price	Rice price
	OLS	IV	IV	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log yield growth, t	-.17***	-.75***	-.93**	-.81***	-.12	-.83**	.12
	[-3.01]	[-2.90]	[-2.47]	[-2.77]	[-.48]	[-2.15]	[.38]
Log yield growth, t-1	-.13***	-.69**	-.60	-.80*	-.47***	-1.11**	-.53*
	[-2.68]	[-1.97]	[-1.42]	[-1.83]	[-3.51]	[-2.21]	[-1.91]
Log exchange rate growth, t	-.17*	-.20*	.04	-.21*	.14	-.32**	.06
	[-1.76]	[-1.80]	[.21]	[-1.86]	[.76]	[-1.43]	[.37]
R-Squared	.32	-.20	.00	.00	.08	.01	.04
Observations	1,103	1,103	1,283	1,020	732	670	968

Notes: T-statistics are in brackets. Each observation is a country-year. The sample includes all countries, because the effect of productivity shocks on crop prices exists with magnitudes not very different across income levels (see column 5 in Table 2). The sample refers to 1961 – 2008, and area-weighted rainfall is used as instrument. Each regression includes country and year fixed effects. Robust standard errors are clustered by country. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A.5 Two-country Model
(A 15% decrease in agricultural productivity in home country)

Foreign country size	Changes in home country equilibrium		
C	$\%\Delta L^*_{a,H}$	$\%\Delta L^*_{m,H}$	$\%\Delta q^*_{m,H}$
0.01	+ 11%	- 56%	- 53%
0.20	+ 2%	- 22%	- 21%
0.25	+ 1%	- 8%	- 7%
0.30	- 1%	+ 11%	+ 10%
0.35	- 2%	+ 36%	+ 34%
0.50	- 5%	+ 225%	+ 209%

Note: C indicates the size of the foreign country relative to the home country (e.g., $C = 0.01$ means that the foreign country's size is 1% of the home country's size).

Table A.6. Changes in aggregate TFP
(A 15% decrease in agricultural productivity)

Country	Baseline model			Small open economy model		
	Productivity effect (1)	Share effect (2)	%ΔTFP (3)	Productivity effect (1)	Share effect (2)	%ΔTFP (3)
Ethiopia	- 11.32%	- 2.21%	- 13.54%	- 11.32%	+ 3.77%	- 7.56%
Ghana	- 7.51%	- 1.38%	- 8.89%	- 7.51%	+ 4.16%	- 3.34%
Malawi	- 7.33%	- 1.35%	- 8.68%	- 7.33%	+ 4.14%	- 3.19%
Bangladesh	- 3.38%	- .57%	- 3.94%	-3.38%	+ 2.69%	- .69%
India	- 3.59%	- .61%	- 4.19%	-3.59%	+ 2.81%	- .78%
Portugal	- 1.79%	- .27%	- 2.1%	-1.79%	+ 1.59%	- .2%
United States	- 0.77%	- .1%	- .9%	- .77%	+ .74%	- .04%

Table A.7 Rainfall and Crop Yield (first-stage results, 1961-2008)

	Dependent variable: Crop yield, t (in log growth rates)					
	Sub-Saharan Africa only	GDP per capita < $4,000	GDP per capita < $10,000			GDP per capita > $10,000
				Sub-Saharan Africa Excluded	Northern hemisphere	
	(1)	(2)	(3)	(4)	(5)	(6)
LogRainfallGrowth, t	.46*** [8.97]	.36*** [12.69]	.28*** [12.97]	.21*** [9.10]	.26*** [9.11]	.08*** [3,50]
TropicalRegion × LogRainfallGrowth,t	-.68 [-1.65]	-.31*** [-4.85]	-.23*** [-4.68]	-.15*** [-3.26]	-.17** [-2.21]	-.23 [-.79]
LogRainfallGrowth,t-1	.03 [.06]	.06** [2.07]	.03 [1.31]	.03 [1.23]	.03 [1.16]	.01 [.37]
TropicalRegion × LogRainfallGrowth,t-1	.05 [.12]	-.03 [-.52]	-.01 [-.22]	-.01 [-.12]	-.01 [-.19]	-.07 [-.24]
R-squared	.17	.12	.09	.07	.10	.12
Observations	1,119	2,378	3,457	2,338	1,790	1,259

Notes: T-statistics are in brackets. Each observation is a country-year. 'Northern hemisphere' represents the countries with latitude greater than 10. Each regression includes country and year fixed effects. *** p < 0.01, ** p < 0.05, * p < 0.1.

Table A.8 Manufacturing output (second-stage results, 1961-2008)

	Dependent variable: Manufacturing output, t (in log growth)							
	Northern hemisphere					All countries		
	all		low credit		agricultural	low credit		
			all	PGDP < $4,000		low trade	high trade	agricultural
	OLS (1)	IV (2)	IV (3)	IV (4)	IV (5)	IV (6)	IV (7)	IV (8)
Log yield growth, t-1	.07** [2.15]	.20* [1.72]	.30* [1.75]	.24* [1.93]	.27** [2.16]	.33** [2.42]	.15 [.35]	.45*** [2.72]
Log yield growth, t	.10** [2.05]	-.08 [-.49]	.03 [.18]	.31* [1.93]	-.01 [-.08]	.01 [.04]	.27 [.33]	.06 [.31]
Log exchange rate growth, t	-.36*** [-3.12]	-.35*** [-3.09]	-.49*** [-4.27]	-.63*** [-3.49]	-.49*** [-4.09]	-.18** [-2.27]	-.35*** [-2.95]	-.54*** [-4.77]
R-squared	.19	.13	.22	.26	.19	.15	.49	23
Observations	1,229	1,229	769	495	878	647	302	745

Notes: Each observation is a country-year. 'Agricultural' represents observations with shares of agriculture production out of GDP greater than 10%. 'Low trade' represents observations with export shares in manufacturing output less than 20%. 'Low credit' represents observations with private credit (% of total GDP) less than 30%. Each regression includes country and year fixed effects. Robust standard errors are clustered by country. *** p < 0.01, ** p < 0.05, * p < 0.1

Table A.9 Employment in Manufacturing (second-stage results, 1961-2008)

	Dependent variable: Employment in Manufacturing, t (in log growth rates)								
	GDP per capita < $10,000						GDP per capita < $4,000		GDP per capita > $10,000
	Northern hemisphere				Northern hemisphere*	Equator	Northern hemisphere	Northern hemisphere*	Northern hemisphere
		baseline	Sub-Saharan Africa Excluded	low credit					
	OLS	IV			IV	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log yield growth, t	.05** [2.26]	.14** [2.35]	.11* [1.87]	.14** [2.13]	.10* [1,75]	-.14 [-1.08]	.21*** [2.62]	.13** [2.37]	-.35 [-1.50]
Log yield growth, t-1	.02 [.70]	-.06 [-1.16]	-.05 [-.86]	-.07 [-.98]	-.03 [-.41]	.02 [.34]	-.01 [-.17]	.08 [.94]	-.18 [-.63]
Log exchange rate growth, t	-.04** [-2.17]	-.05** [-2.51]	-.05*** [-2.88]	-.02 [-.89]	-.05** [-2.56]	-.02 [-.98]	-.02 [-.76]	-.03 [-.82]	-.06 [-1.27]
R-squared	.16	.09	.12	.14	.14	.08	.07	.18	--
Observations	1,043	1,043	992	609	771	1,036	638	427	888

Notes: T-statistics are in brackets. Each observation is a country-year. 'Northern hemisphere (Northern hemisphere*)' stands for the countries with latitude greater than 10 (20). 'Equator' stands for the countries whose latitude is between -20 and 20. 'Low credit' represents observations with private credit (% of total GDP) less than 30%. Each regression includes country and year fixed effects. Robust standard errors are clustered by country. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.10 Capital investments in manufacturing (second-stage results, 1961-2008)

	Dependent variable: Capital investment in Manufacturing, t (in log growth rates)					
	GDP per capita < $10,000			GDP per capita < $4,000	GDP per capita < $15,000	GDP per capita > $15,000
			low trade			
	OLS (1)	IV (2)	IV (3)	IV (4)	IV (5)	IV (6)
Log yield growth, t-1	-.06 [-.54]	1.31* [1.92]	1.49 [1.61]	1.43* [1.73]	1.16* [1.72]	-.14 [.41]
Log yield growth, t	-.10 [-.98]	.56 [.67]	1.79 [1.64]	.07 [.09]	.38 [.51]	-.40 [-1.22]
Log exchange rate growth, t	-.27*** [-3.75]	-.24*** [-3.05]	-.23** [-2.11]	-.46*** [-3.43]	-.24*** [-3.45]	-.1.00*** [-8.30]
Observations	1,004	1,004	481	555	1,189	701

Notes: T-statistics are in brackets. Each observation is a country-year. 'Low trade' represents observations with export shares in manufacturing output less than 20%. Each regression includes country and year fixed effects. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.11 List of 118 countries

Afghanistan	Germany	Kazakhstan	Poland
Angola	Denmark	Kenya	Portugal
Albania	Dominican Republic	Kyrgyz Republic	Paraguay
United Arab Emirates	Algeria	Cambodia	Romania
Argentina	Ecuador	Korea, Rep.	Russian Federation
Armenia	Egypt, Arab Rep.	Lao PDR	Sudan
Australia	Eritrea	Liberia	Senegal
Austria	Spain	Libya	Somalia
Azerbaijan	Estonia	Sri Lanka	Suriname
Burundi	Ethiopia	Lithuania	Slovak Republic
Belgium	Finland	Latvia	Slovenia
Benin	France	Morocco	Sweden
Burkina Faso	Gabon	Madagascar	Syrian Arab Republic
Bangladesh	United Kingdom	Mexico	Thailand
Bulgaria	Georgia	Mongolia	Tajikistan
Bolivia	Ghana	Mozambique	Tunisia
Brazil	Greece	Malawi	Turkey
Botswana	Guatemala	Malaysia	Tanzania
Central African Republic	Honduras	Nigeria	Uganda
Canada	Croatia	Nicaragua	Ukraine
Switzerland	Haiti	Netherlands	Uruguay
Chile	Hungary	Norway	United States
China	Indonesia	Nepal	Venezuela, RB
Cote d'Ivoire	India	New Zealand	Vietnam
Cameroon	Ireland	Oman	Yemen, Rep.
Congo, Rep.	Iran, Islamic Rep.	Pakistan	South Africa
Colombia	Iraq	Panama	Zambia
Costa Rica	Italy	Peru	Zimbabwe
Cuba	Jordan	Philippines	
Czech Republic	Japan	Papua New Guinea	