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

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Abstract

This paper shows how agricultural productivity shocks can generate large industrial output fluctuations in developing countries, using static general-equilibrium models with Stone-Geary preferences. A negative shock to agricultural productivity increases food prices, which affects manufacturing output through two channels: (1) Meeting subsistence requirements in the face of rising food prices causes poor households to shift consumption away from manufactures; (2) Capital and labor move away from manufacturing and into agriculture in response to the food price increase. As a result, manufacturing output decreases in response to the decline in agricultural productivity. This effect depends on income levels and openness to trade. Using annual manufacturing data and rainfall shocks as 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 50% of industrial output fluctuations in developing countries (rainfall shocks cause 11% of the fluctuations). Lastly, this paper further argues that such perverse phenomena, in which resources move toward the sector with declining productivity, may lead to a significant reduction in aggregate productivity.

Key Words: Output Volatility, International Trade, Economic Development, International Comparisons, Agriculture

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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 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 causes of fluctuations is important especially for developing countries.

This paper is part of a growing literature that studies industrial output fluctuations 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).

[1] Regressing volatilities (over the period 1960-2008) on log per capita GDP and log population reveals that a 10% decrease in per capita GDP is associated with a 0.3 units (or, 30 percent of the total GDP) increase in industrial output volatility and a 0.07 units 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. Meanwhile, 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).

In contrast, this paper provides a novel explanation for industrial output fluctuations highlighting demand-side reasons. I use a prominent characteristic of developing economies – a 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 literature does not use non-homothetic preferences, has only manufacturing-type sectors in the models, and relies mainly on the size of shocks (e.g., productivity shocks, 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 us 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 model generates differing flows of labor and capital resources depending on the assumption about the economy. Under the closed economy, 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 capital and labor resources move away from manufacturing and into agriculture, further reducing manufacturing output. Perversely, the economy shifts resources toward the sector with declining productivity, sharply curtailing aggregate productivity in the economy. This effect becomes stronger the closer is the country to the subsistence level, which causes 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 and generate a negative correlation.

[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 they focus 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.

To address the endogeneity issue, I use cross-country panel data which includes 113 countries for the period 1970-2002, and regress changes in manufacturing output on changes in yield, employing rainfall shocks as instrument for yields. I construct area-weighted rainfall, crop-area weighted rainfall, and non-crop area rainfall, using the GIS (Geographic Information System) software. The first two rainfall data have 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 leads to a 3.1% decrease in manufacturing output. Overall, crop yield variation can explain up to 50% of industrial output fluctuations in developing countries (rainfall shocks through yields cause 11% 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, 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] Second, I find that exogenous declines in crop yield result in significant declines in both employment and capital investment in manufacturing in developing countries. The strength of this effect, especially on employment, is found to be greater for countries whose planting cycles are seasonal rather than year-round, which serves as strong evidence for the resource channel.

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 becomes larger, and the link eventually changes the sign (and becomes 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 get 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 Donaldson (2012), and Caselli et al. (2012), which argue that reductions in trade barriers not only lead to lower fractions of the workforce employed in subsistence

[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.

agriculture characterized by low productivity, but also lessen real income volatility.[8]

Likewise, this paper is 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; Matsuyama, 1991). Their primary focus is on 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 my paper is that their observation is a district which can be considered as small open economy, while observation in this paper is a country which is 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 is able to provide 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 the authors focus on microeconomic evidence within a single country.

Another closely related is the paper by Da-Rocha and Restuccia (2006). Like this paper, the authors use a two-sector model in which one sector's productivity shocks affect the other sectors' output through the 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 the authors use homothetic preferences, I use non-homothetic preferences, and in my model, income effects dominate substitution effects.

Lastly, many papers in empirical development literature use rainfall shocks as a source

[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.

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 on 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.

The remainder of the paper is organized as follows. Next section 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 under the closed economy 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. There exists L mass of population, each endowed with one unit of labor and $\frac{K}{L}$ units of capital. In this section, we assume $L = 1$ for simplicity.

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 the 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 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 agricultural good, and then allocates the residual income $I - p_a \gamma_a$ on 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 us 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, we 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 is, the lower is 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, 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, is the elasticity of manufacturing output with respect to agricultural productivity higher in low-income countries? We have seen that food price elasticity of manufacturing demand decreases with income levels. Similar patterns hold in 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 contributes to higher levels of industrial output volatility in poor countries. Another important implication is that resources are moving toward agriculture when its productivity is declining. Such reallocation of resources may result in a sharp reduction in aggregate productivity. 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 large reduction in aggregate productivity as resources move toward the sector with declining productivity. This effect decreases with income levels (See Appendix B).

The three implications will remain as core theoretical predictions throught 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 we 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 was that consumers spend constant shares (α and $1-\alpha$) of their residual income $I - p_a\gamma_a$ on food and manufacturing, regardless of changes in the price. 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), we obtain the food price elasticity of manufacturing expenditure as follows,

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

where η_{p_a} was 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 manufacturing. Since p_a is inversely related with 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 $\tilde{G}(L_m) = \frac{\lambda_2(p_a)\cdot L - L_m}{[L + \frac{(\beta_m - \beta_a)}{\beta_a(1-\beta_m)} L_m]^{\beta_a}}$; $\lambda_2(p_a(L_m)) = \frac{\widehat{\alpha_m}(\sigma, p_a)(1-\beta_m)}{\widehat{\alpha_m}(\sigma, p_a)(1-\beta_m) + \widehat{\alpha_a}(\sigma, p_a)(1-\beta_a)}$; $p_a(L_m) = \frac{z_m \beta_m}{z_a \beta_a} [\frac{\beta_a(1-\beta_m)L + (\beta_m - \beta_a)L_m}{K}]^{\beta_a - \beta_m} [\beta_m(1-\beta_a)]^{\beta_m - 1} [\beta_a(1-\beta_m)]^{\beta_a - 1}$. 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, as 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? 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 one. 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.[10] 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).[11] 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.[12] 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.

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

[11] 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.

[12] 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.

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.[13] To justify the usage of yields for agricultural TFPs 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, includes 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 cultivation 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.

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 the year 2004 is 91%, while it is only 7% in Ethiopia.[14] I plug these numbers back in 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 $\alpha = 0.02$ and $\gamma_a = 0.93$.

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 88% in Ethiopia, while it is only 4% in the US (see columns 1, 2, and 3 of Table 2). To summarize, Table 1 presents the assigned parameter values and the data source.

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

[14]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 fall in agricultural productivity is pulling factors out of only manufacturing (not services). One way to solve this problem is to treat manufacturing and services as an aggregate.

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.[15] 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 their income for the subsistence food requirement, on the production side a large share of labor and capital resources has to be devoted to agriculture (column 4 of Table 2).

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 higher profits, thus 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.[16]

Perversely, 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, when the initial period equilibrium price (before the 15% productivity shock) is used as a base price for each country. For example, in Ghana, the share effect is -1.4% out of a -8.9% change in aggregate TFP, and the effect becomes negligible in rich countries.

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, manufacturing output volatility of a country can be large because of two reasons: The large size of shocks and the country's income close to the subsistence level. First, I measure the size of shocks by calculating the standard devi-

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

[16] 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 level of subsistence.

ation 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, while Bangladesh exhibits the lowest.

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 (column 3). One of the reasons can be associated with the closed economy assumption in the baseline model. In section 5, I show how the magnitudes can be attenuated in open economy models. Lastly, note that countries that are subject to large size shocks exhibit higher manufacturing output volatility. For example, even though Portugal is much richer than Bangladesh, Portugal's implied volatility is only slightly higher mainly because crop yield volatility is three times higher in Portugal.[17]

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 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 over 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 to compare with the baseline model results.

The 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 17.194% in the baseline model, while it decreases by 17.288% (18.467%) 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 about 0.002% increase in manufacturing output in response to the increase in food prices. Note that due to the small utility weight attached to agricultural products ($\alpha = 0.02$), the substitution effect caused by agricultural shocks is also small. I show in

[17] 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.

Appendix A.2 that interesting volatility patterns will be generated, when α becomes 0.5 (which is far from the reality).

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 levels. To test these predictions, we need exogenous movements in agricultural productivity which vary across countries and time. I use crop yields as 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 which captures country specific time trends of manufacturing output such as technological progress; α_t is a country fixed effect ; $\epsilon_{c,t}$ is an idiosyncratic error term. 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 industry 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 an upper-hemisphere country 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 seasonality consideration is indeed very important for the results.

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, there still remains such effect, which can be quantified using a simple model from Jones (2011) and OECD input-out data across countries.[18] I find

[18] Using the model from Jones (2011), we can show $log(\Delta y) = (I - B')^{-1} log(\Delta Z)$, 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

that, on average across developing countries with per capita GDP less than \$10,000 (in 2005 international dollars), a 10% increase in agricultural productivity is still associated with about 0.3% increase in manufacturing output excluding food, tobacco and textile related sectors. When including all sectors, 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 analyzing the 0.3% part as future work due to 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 portion of the estimate effect. Two, input-output data and portions of agricultural inputs are largely different across countries and even within developing countries, but the data is available only for a small fraction of developing countries.

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 and aggregate output.

Using the simple framework (10) 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 variables such as the share of agriculture, the level of financial development, and openness to trade. These variables are highly correlated with each other, while there are only 113 countries in the data. Hence, I instead run separate regressions on different groups of countries depending on income levels and the other variables.

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 prices data and manufacturing data on employment and capital investment, I test the channels using similar frameworks:

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

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

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

Similarly to the main estimations, these specifications are tested on different groups of countries with varying income levels, latitudes, openness to trade, shares of agriculture, and credit

across sectors (only agricultural productivity changes from 1 to 1.1).

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 it is consistently available for many countries and time periods. However, yields differ from pure total factor productivity (TFP) measure, because it also depends 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 TFP. Detailed studies of agricultural production show that yields are sensitive to changes in rainfall and changes in temperature (e.g., Lobell et al. 2007; Schlenker et al. 2009). I use only rainfall shocks, as some studies show that heat may affect manufacturing workers' productivity and output in warm-weather countries (Dell et al. 2012; Jones and Olken 2010; Colmer 2016; Chen 2003).[19] Admittedly, rainfall is correlated with temperature (Trenberth and Shea 2005). But, how rainfall affects manufacturing production through temperature is ambiguous: even in warm weather increases in humidity may worsen workers' productivity despite lower temperatures caused by rainfall. Similarly, Santangelo (2016) finds that in India the effect of rainfall outside main growing season on manufacturing is statistically not significant. In this paper, a simple solution might be the inclusion of temperature changes in the main estimating equation. However, this will not be appropriate, as the data covers countries with wide range of latitudes: increases in temperature have opposite effects on productivity depending on the season in higher latitude countries. Thus, aggregating temperatures annually will be problematic for countries with four seasons (note that the data on manufacturing is annually reported). This type of analysis is more appropriate when focused on local environments that have warm weather all year round. For example, Burgess et al. (2013) and Colmer (2016) study how temperatures affect mortality and output across districts in India.

In order to ensure that rainfall affects manufacturing output through affecting yields and not through other channels, I perform several robustness checks. First, I find that labour

[19] Jayachandran (2006) also uses crop yield as 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.

movement effect in response to agricultural productivity is stronger and highly significant in countries with agricultural seasonality. Plus, I find that labour productivity in manufacturing hardly changes in response to rainfall, which is strong evidence that rainfall effects on industrial output through temperature may not exist. Second, results using rainfall applied to non-crop areas exhibit much weaker effects (note that non-crop area rainfall is still correlated with crop-area rainfall, although the effect on yield is weaker). This result highly weakens the possibility 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 $X_{c,t} = excessRain_{c,t} \cdot \Delta rain_{c,t} + tropic \cdot \Delta rain_{c,t} + tropic \cdot \Delta rain_{c,t-1}$; $\Delta rain_{c,t} = ln\frac{rain_{c,t}}{rain_{c,t-1}}$; η_c and η_t country and year fixed effects ; $u_{c,t}$ is the error term. I include $X_{c,t}$ in order to allow for non-linear effects of rainfall. Note that positive effects of rainfall on yield may decrease as the level of rainfall increases. I control for this in two ways. First, I construct the dummy variable $excessRain_{c,t}$ which takes one if rainfall in year $t-1$ exceeds 120% of average rainfall in the country. Interacting this with the current year rainfall growth captures such a country specific nonlinear effect. Second, I also include interaction terms with tropical region dummy which is equal to 1 if the country has a tropical climate, to take into account climate-specific nonlinear effects. 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 INDSTAT2 version that reports the data according to the two-digit ISIC Revision 3 classification, for the period 1970-2002.[20] Although the original UNIDO data set 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 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 tobacco) and sector 2 (textile related industries which 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 less than 5 consecutive year observations (in the number of employees, as this has less missing values than output and investment)

[20]The results are also robust to using longer time-series 1960-2008 (see Appendix Tables A.6-10). Estimating 50 years of time series data across countries might be too extensive due to rapidly changing world economy situation. Also, it's reasonable to consider the period before the onset of the unprecedented food crisis in 2007-8.

and combining with other data, I have 113 countries in the analysis.

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 to have a sense on how volatilities may differ between poor and richer countries. First, we see that output and employment (capital investment) grew about 5% (25%) annually on average during the period 1970-2002 (see column 1 in Table 5). Second, volatilities are more than three times higher for employment and capital investment, and more than doubled for output, in poor countries (mean GDP per capita less than $4,000) than in higher-income countries (mean GDP per capita greater than $10,000). Note that this paper's aim is to analyze causes of such volatility patterns.

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 the Year 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 this 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 the area of grid cell is smaller at higher latitude degrees on the globe. Lastly, another data layer that contains the world country borders information is taken from the Thematic Mapping world borders dataset. This does not include small countries which do not fully contain any single grid cell (0.5×0.5 degree resolution), so all such small countries are naturally dropped in 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 on 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 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 measure of agricultural productivity. The data comes from the FAOSTAT and includes major staple crops such as wheat, rice, maize, barley, oats, rye, millet, etc. Crop prices 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 that 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.

Rows 4-6 in Table 5 show cross-country average values of within-country mean and volatilities in rainfall growth. We see 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 in yield (see row 7) is significantly higher in poor countries (GDP per capita less than $4,000) at about 28%, compared to higher-income countries (GDP per capita greater than $10,000) volatility around 16%. A plausible explanations can be 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 system. There can be many other reasons other than rainfall, such as higher sensitivity in temperature and larger shocks to intermediate inputs in developing countries. Accordingly, the table (rows 9-14) shows that crop price tends 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 COMTRADE data. The following two datasets are taken from the World Bank database: the share of agricultural value added as a share of GDP, 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.

5 Estimation Results

5.1 First Stage Results (rainfall and crop yields)

Table 6 shows the first-stage relationship between yields and rainfall, with the crop-area weighted rainfall used as main instrument. I find that an increase in rainfall tends to raise yields in developing countries: A 10% increase in rainfall leads to a 3% increase in yield in countries with per capita GDP less than $10,000 (column 3). To control for 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) interacted with the rainfall growth. The results show that a tropical climate reduces the positive effect of rainfall on yield by more than 80%. In addition, to examine non-linear effects of rainfall, I construct three excessive rain dummies which take 1 if rainfall in the previous year exceeded 110%, 120%, or 130% of average rainfall in the country over the period 1970-2002. The dummies are interacted with rainfall growth, and the results in columns 2-5 show that the positive rainfall effect on yield growth decreases by more than 30%, if it had sufficient rainfall in the previous year. We see that the specification including the 120% excess-rain interaction term leads to the most significant result. Hence, specifications 1, 3, and 6 are used as first-stage estimation framework.

When I restrict the sample with per capita income below $4,000, the positive relationship between current year rainfall and yields become even stronger: A 10% increase in rainfall leads to a 3.7% increase in yield (column 1 in Table 6). As for higher income countries with per capita income greater than $10,000, the effect decreased by more than 60% (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 30, implying that rainfall is a strong instrument for yields in developing 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 level of subsistence. 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). Column 1 reports the OLS result for countries with per capita income less than $10,000 (in 2005 international dollars). The estimate on lagged yield growth, which is the elasticity of manufacturing output with respect to yield, is 0.08. Meanwhile, the IV estimate (column 2 in Table 7) for the same coefficient is 0.18. 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 smaller than 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 Table 7 results is that only the coefficients on lagged yield growth are significantly positive, while the current yield growth registers insignificantly. As mentioned in section 4.1, a plausible reason may relate to agricultural seasonality – especially for upper hemisphere countries – and a time lag between an agricultural shock and its impact on manufacturing. Indeed, columns 3 and 4 show that the lagged yield coefficients become even stronger as the sample gets restricted to upper-hemisphere countries with minimum latitude at 10 degrees and 20 degrees. Especially, the regression result with the 20-degree latitude cut (column 4) implies that a 10% increase in yield leads to a 3.1% increase in manufacturing output, which is highly significant at the 1% level. On the other hand, the result is weak over the sample countries near the equator between -20 and 20 degree latitudes (column 5). This result is highly 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 result on employment will be shown in next subsection.

The core theoretical prediction of this paper is that the income effect is stronger when the income level is close to the level of subsistence. So far, we have seen 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 with per capita income less than $4,000, the IV estimate on lagged yield growth becomes larger (column 6 in Table 7). On the other hand, consistent with the theory, column 7 shows that the estimate becomes insignificant for higher income countries (per capita income greater than $10,000).

We next examine how other variables such as the share of agriculture, financial development, and openness to trade affect the strength of the model's predictions.[21] First, the theory implies that the role of agricultural productivity will be stronger when the share of agriculture is large. Consistently, column 2 of Table 8 points to a larger and significant estimate on lagged yield growth when the sample is further restricted by agricultural shares greater than 20% in total GDP. Second, another very important implication associated with the open economy model (see section 6) is that the strength of the positive link will decrease with the openness to trade. To investigate this, I restrict the sample to countries with low openness to trade (the export share in manufacturing output less than 20%), and I find that the estimate on lagged yield growth becomes even larger and statistically more significant at the 1% level (column 3). In contrast, the positive link becomes insignificant when the sample countries are relatively more open to trade (column 4). Both results well support the theoretical prediction.

Third, 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 – was to pull 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 lagged yield growth jumps to 0.28 from 0.19

[21] 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 113 with less than 2000 observations in total, including all those relevant measures in the estimation leads to multicollinearity.

with the 1% level significance (column 5 of Table 8).

Lastly, 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 instrument with the same first-stage specification as before. Although crop-area rainfall and non-crop area rainfall are highly correlated, the first-stage F-statistics decreases by more than 20%. Columns 6-8 (Table 8) show that the second-stage results using non-crop area rainfall become less significant, which weakens the possibility of other channels.

Predicted industrial output volatility — Finally, we investigate contributions of rainfall shocks to yield on industrial output fluctuations. Table A.3 reports standard deviations of predicted manufacturing output growth rates based on the previous IV estimation result (column 4 of Table 7) for upper-hemisphere developing countries (per capita GDP less than $10,000). In other words, predicted manufacturing output growth rates are obtained from the following equation,

$$\widehat{\Delta q^m_{c,t}} = \alpha_c + \beta_0 + \beta_1 \cdot \Delta\widehat{yield}_{c,t} + \beta_2 \cdot \Delta\widehat{yield}_{c,t-1} + \epsilon_{c,t} \ ,$$

where $\Delta\widehat{yield}_{c,t}$ and $\Delta\widehat{yield}_{c,t-1}$ are predicted values from the first-stage estimation given the data on rainfall shocks.[22] The average value of such volatilities for developing countries is found to be about 2% (column 1 of Table A.3). The manufacturing output volatilities calculated directly from the UNIDO data are also presented in column 2, and the average value for developing countries is about 17%. The values in column 3 are obtained simply by dividing the column 1 values by column 2 values (Table A.3). The average of such ratios for the developing countries is 0.11. This suggests that crop yield variation induced by rainfall shocks can explain about 11% of manufacturing output fluctuations in developing countries, if we assume that rainfall shocks are uncorrelated with other shocks that affect manufacturing.

Note that this paper's aim is not on the rainfall effect but is on the effect of overall agricultural productivity shocks on manufacturing volatility. One may argue that the 11% portion in volatility does not look important. However, it is only about rainfall effect. There are other important factors that affect agricultural production such as temperature and access to intermediate inputs. If we have a strong assumption that all the variations in the yield data are not correlated with shocks to manufacturing, about 50% of manufacturing output volatility on average can be explained by the yield variations in the developing countries (this volatility is calculated using only the second-stage result in column 4 of Table 7, plugging in the yield growth - from the data and not the estimated ones from the first stage).

5.3 Estimation Results on Mechanism

Importantly, the theoretical model suggests that agricultural productivity affects manufacturing output through the resource reallocation channel. When there is a negative shock

[22] In this specification, I do not include the exchange rate covariate, because the source of output growth fluctuations needs to be changes in yield only. Moreover, the estimation results of regression (4) in Table 7 on yields are highly robust to the exclusion of the exchange rate variable.

to agricultural productivity, a drought as an 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. Additionally, I show results on the negative relationship between domestic food price and productivity.

Labor movement between sectors — Labor reallocation effect is a very important channel in this analysis, as developing countries are labor abundant and most industries are labor intensive. Hence, workers movement between 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 especially limited by many factors such as time, space, and willingness to migrate. To illustrate, an agricultural worker in an upper-hemisphere country has 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), with minimum latitude cuts being varied. The IV result implies that a 10% decrease in current year yield leads to a 2.4% decrease in manufacturing employment in the same year at the 1% level significance, for upper-hemisphere developing countries located above 20-degrees latitude, with per capita income less than $10,000.[24] When the minimum latitude cut is lowered to 10 degrees in the upper hemisphere, the effect slightly decreases to 2.1%. Moreover, for countries that are located near the equator (between -10 and 10 degree latitudes), the results become insignificant, which is consistent with the previous result on output.[25] These results that are 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.

Next, I find two interesting results associated with credit constraints and strong income

[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 similar situation in developing countries today.

[24]Note that, unlike other regression results, it is the coefficient on current yield growth that is significantly positive, while the coefficient on lagged yield is near zero. To see this, suppose that a positive shock to yield occurred in year t and one worker moved from agriculture to manufacturing after the harvest in the same year t and continue to work in the industry until the next year t+1 before the next harvest. Now, the number of employees in manufacturing is 11 both in t and t+1, while it is still 10 at time t-1. Thus, log employment growth is log(11/10) at time t while it is log(11/11) = 0 at time t+1. Basically, the positive agricultural shock occurred in year t appears to affect the employment growth in year t positively, while the same shock in year t has no effect on the employment growth in year t+1. Thus, this example explains why the coefficient on current yield growth is significantly positive while the coefficient on lagged yield growth is close to zero.

[25]It is highly possible that the resource reallocation pattern still exists in countries near the equator. The main reason for the insignificant estimation result can be that the agricultural seasonality near the equator may not be well aligned with the annual calendar data (for example, probably rainfall from previous year June to next year March affects crop yields that are mostly harvested in May).

effects. First, columns 2 and 3 in Table 9 show that both magnitude and statistical significance of the effect substantially increase in countries with relatively poor credit systems (private credit less than 30% of GDP): The effect on manufacturing employment in response to a 10% increase in productivity rises from 2.1% to 3% (with almost doubling t-statistics from 3.1 to 5.9). This result is consistent with the implication of the theoretical mechanisms as well as the previous estimation result on output with the same credit constraint (column 5 in 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 cut is lowered to $4,000, the labor reallocation effect for upper-hemisphere countries increases by more than 35%, with even higher statistical significance. A plausible explanation for this phenomenon is that workers have higher willingness 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 higher income countries (per capita income greater than $10,000). These results are consistent with the main theoretical implication that the role of agriculture on resource reallocation diminishes with income levels.

Lastly, note that the simple OLS result for upper-hemisphere countries is positive and significant, but the magnitude is much lower than the IV result (columns 1 and 2 of Table 9). The same pattern was observed in the previous estimation results on output in Table 7, and the same reason applies in this context, too. Manufacturing and agriculture compete for the limited amount of labor in the economy. Therefore, higher employment in manufacturing can be linked to lower yield due to lower labor input, leading to the downward bias of the OLS result.

Table 10 displays sector-specific regression results (total eight sectors, see Table A.2 for descriptions) in developing countries, with the same estimation structure used above. Interestingly, the wood products industries, which are highly labor-intensive, exhibit a highly significant effect: A 10% decrease in agricultural productivity results in a 5.6% 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 incentive to keep their workers, because costly capital assets need to be operated continuously to cover the cost. Meanwhile, employment in textiles registers insignificantly despite its labor intensiveness, possibly due to its high volume of exports.

Capital investment allocations — Table 11 displays results of estimating Equation (13) which explores the relationship between yields and capital investment in manufacturing. The IV result in column 2 implies that a 1% decrease in previous year yield leads to about 1.5% decrease in capital investment in manufacturing in developing countries (per capita income less than $10,000). Comparing with the column 1 result, we see the downward bias of the OLS result. This pattern is consistent with the previous results on output and employment. These results support for the theoretical mechanism that some capital reallocates out of manufacturing in response to a decrease in agricultural productivity.[26] Admittedly, we 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).[27] 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 become 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 and basic metals and equipment) are highly responsive to changes in agricultural productivity in developing countries. Meanwhile, 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 especially for the wood-products industry, while other capital-intensive industries registered insignificantly. These flipping results on sector-level analysis imply that factor intensity of manufacturing sectors may determine what type of factors move more intensively in response to shocks to agricultural productivity, which strengthens robustness of the results in support of the theoretical mechanism.

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, Table 13 explores the relationship between domestic productivity and cross-country yearly crop prices. As expected, negative shocks to productivity tend to raise food prices. For instance, a 10% decrease in yield induced by rainfall shortages leads to about 9% increase in wheat and barley prices.[28] Both results are highly significant at the 1% level. Results on maize, sorghum, and soybean prices also display consistent results at the

[26]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 lands is managed by individuals or families in developing countries.

[27]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.

[28]Yields in the estimations in Table 13 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.

5% level significance. Note that unlike the previous estimations the regressions in this table are performed over all countries without the restriction with the $10,000 income cut. This is because the extent to which agricultural productivity affects prices is not very different in poor and rich countries, as theoretically confirmed with the previous numerical results (see column 5 of Table 2). Even with the income restriction, the results are still robust (results are not shown). In sum, 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 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 suppressing 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 suppresses the income effect and help 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 the 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 into the domestic market, I show that the effect of domestic productivity shocks gets 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 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 Home country's equilibrium allocations are affected by domestic agricultural productivity shocks, while varying the size of 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

$$U_c = (q_{a,c} - L_c \gamma_a)^\alpha q_{m,c}^{1-\alpha}, \quad c = H, F. \tag{15}$$

Given the aggregate preferences, we can solve the utility maximization problems for each country as if there is 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 the 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 Home country change as the size of Foreign country varies? To address this question, I simulate the model and investigate how an agricultural shock in Home country affects resource reallocations differently depending on the size of Foreign country. For simplicity, we assume that 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 Foreign country is bigger than 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 size.[29] Table 14 shows changes

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

in equilibrium allocations when Home country is subject to a 15% decrease in agricultural productivity. 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 Foreign country size increases, and eventually the link changes the sign. The last three rows show that resources flow in 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 the positive link and (2) the comparative advantage effect which causes the 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 goods 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:

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

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 un-weighted 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% – in-

[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.

crease 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, only 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 toward locally-abundant foods (Atkin, 2012), (2) high transportation costs as food is bulky and heavy (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 lead to imperfect pass-through of international prices. Hence, domestic supply and demand still play a crucial role in determining equilibrium prices and output. Accordingly, we may expect that the direction of the baseline model (closed economy) results still holds, but 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 of Home foods, which is associated with the above explanation by Atkin (2012). This allows us to fit the model to the empirical observation on the imperfect pass-through of international food prices.

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

[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).

[32]If we assume that domestic food can be exported, 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 much to learn, as most developing countries are small open economy net food importers.

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:

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

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

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

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, we 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) in Equation (21), we 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 us $\sigma \approx 5$. For simple comparison, I fix the world price $p_{a,w}$ at the equilibrium price of the baseline model, and $z_{a,c}$ that 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 Malawi, this model generates a 4.6% decrease in output, whereas the baseline model generates a 16.4% decrease. This leads to a much closer match to the econometric estimation result in the previous section, which predicts about 4.1% decrease in output for developing countries (column 6 in Table 7).

7 Concluding Remarks

This paper identified a novel mechanism in 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. 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 levels, and that the degree of output fluctuations also decreases with income levels.

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 the growth of the economy. 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 within agriculture but also partly compensated by producing more manufacturing goods.

The implication for international food trade is relevant in light of recent developments. First, researchers have shown that climate changes will increase the frequency and severity of droughts as well as the temperature. 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 (in which, for example, international prices for rice increased by 160% within a year), countries try to insulate the domestic markets from the 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 re-establishing 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 average yield	FAO (1970 – 2002)
$\boldsymbol{\alpha}$	0.02	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))
$\boldsymbol{\gamma_a}$	0.89	Utility subsistence parameter	

Notes: Values in the brackets represent ranges of country- or time-specific parameters (c denotes a country, t denotes time). 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	0.88	0.07	+ 22.4%	- 57.8%	- 50.8%	- 53.9%
Malawi	2.14	1.19	0.57	0.31	+ 20.5%	- 20.8%	- 13.0%	- 16.4%
Ghana	3.00	1.04	0.58	0.30	+ 20.6%	- 21.7%	- 13.7%	- 17.2%
Bangladesh	2.84	2.36	0.25	0.63	+ 18.8%	- 6.9%	- 3.1%	- 4.7%
India	6.17	1.73	0.27	0.61	+ 18.9%	- 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%	- 0.9%	- 0.3%	- 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.

Table 3 Simulated volatility

Country	(Data) crop yield volatility (1)	Simulated manuf. output volatility (2)	(Data) manuf. output volatility (3)	Simulated aggregate output volatility (4)	(Data) aggregate output volatility (5)
Ethiopia	12.8%	39.5%	15.9%	7.9%	4.4%
Malawi	18.9%	28.2%	15.4%	10.9%	7.1%
Kenya	13.9%	11.1%	13.1%	6.1%	3.3%
Nigeria	16.7%	40.0%	43.9%	8.8%	3.7%
Ghana	9.2%	29.7%	38.3%	8.1%	5.0%
Bangladesh	5.6%	2.5%	25.1%	1.8%	3.7%
India	6.4%	3.2%	10.3%	2.3%	2.6%
Portugal	16.5%	2.7%	12.8%	2.5%	4.0%
United States	13.5%	.6%	4.7%	.8%	2.2%

Notes: The simulated volatility values (columns 2 and 4) of the baseline model are based on the annual yield data from the FAO (see Table 1). Values in columns 1, 3, and 5 are computed directly from the data. Column 5 values are based on the per capita GDP (in 2005 international dollars) data set, and annual growth rates are filtered by the HP(100) filter to control for time trends of growth rates. 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	CES model			Imperfect pass-through model
	(σ = 1)	σ = 0.52	σ = 0.85	σ = 2.5	
	(1)	(2)	(3)	(4)	(5)
Ethiopia	- 53.904%	-54.426%	-53.953%	- 53.902%	- 11.763%
Malawi	- 16.391%	-17.125%	-16.469%	-16.388%	- 4.607%
Ghana	- 17.194%	-18.467%	-17.288%	- 17.193%	- 4.816%
India	- 5.138%	-6.096%	-5.226%	- 5.136%	- 1.630%
Bangladesh	- 4.723%	-5.41%	-4.802%	- 4.719%	- 1.577%
Portugal	- 2.030%	-3.535%	-2.133%	- 2.029%	- .652%
United States	- .626%	-1.772%	-0.719%	- .625%	- .206%

Table 5 Descriptive statistics

	Mean of cross-country values				
	All countries		GDP per capita < 4000	GDP per capita > 10000	
	Mean (1)	Standard Deviation (2)	Standard Deviation (3)	Standard Deviation (4)	Observations (All countries) (5)
Manufacturing :					
Growth in output (value added)	1.05	.20	.25	.12	2093
Growth in number of employees	1.05	.19	.17	.06	2404
Growth in gross capital formation	1.25	.67	1.01	.26	1486
Rainfall :					
Growth in crop-area rainfall	1.03	.22	.23	.24	3616
Growth in non-crop-area rainfall	1.04	.23	.24	.25	3399
Growth in area weighted rainfall	1.03	.21	.21	.23	3729
Agriculture:					
Growth in cereal yield	1.05	.22	.28	.16	3349
Share of agriculture (% of GDP)	19	4	5.2	1.42	2861
Growth in wheat price	1.05	.39	.76	.12	1140
Growth in maize price	1.10	.39	.30	.14	1400
Growth in rice price	1.13	.49	.46	.14	1039
Growth in soybean price	1.08	.47	.16	.19	732
Growth in barley price	1.04	.36	.79	.12	1057
Growth in sorghum price	1.03	.34	.39	.14	718
Growth in GDP per capita	1.02	.06	.07	.03	3242
Growth in exchange rate to $US	1.47	1.46	1.45	.12	3405
Export share in manufacturing output	38	24	30.7	16.7	2189
Private credit (% of GDP)	38	--	Mean =21.4	Mean =86.6	3333

Notes: The data above has 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. Sample refers to the years 1970-2002, except the six crop prices which refer to 1991-2008 due to limited availability.

Table 6 Rainfall and crop yields (First-stage results)

	Dependent variable: Crop Yield, t (in log growth rates)					
	GDP per capita < $4,000	GDP per capita < $10,000				GDP per capita > $10,000
	(1)	(2)	(3)	(4)	(5)	(6)
LogRainfallGrowth, t	.37*** [10.88]	.31*** [11.12]	.30*** [11.42]	.30*** [12.04]	.29*** [11.18]	.09*** [2.98]
TropicalRegion × LogRainfallGrowth,t	-.37*** [-4.78]	-.26*** [-4.86]	-.26*** [-4.90]	-.26*** [-5.01]	-.26*** [-4.87]	-.37 [-1.52]
ExcessRain1,t × LogRainfallGrowth,t		-.11** [-2.53]				
ExcessRain2,t × LogRainfallGrowth,t	-.17** [-2.42]		-.13** [-2.56]	-.14*** [-2.76]		-.04 [-.71]
ExcessRain3,t × LogRainfallGrowth,t					-.10 [-1.63]	
LogRainfallGrowth,t-1	.00 [.15]	.00 [.23]	.00 [.22]	-.01 [-.27]	.00 [.23]	.04* [1.80]
TropicalRegion × LogRainfallGrowth,t-1	-.04 [-.47]	.00 [.05]	.00 [.05]	.03 [.64]	.00 [.06]	.02 [.08]
Country fixed effects	yes	yes	yes	no	yes	yes
Time fixed effects	yes	yes	yes	no	yes	yes
R-Squared	.14	.10	.10	.07	.10	.09
F-statistics	32.46	37	37.17	37.17	36.27	1.51
Observations	1609	2400	2400	2400	2400	891

Notes: Each observation is a country-year. PGDP represents per capita GDP (in 2005 international dollars). 'ExcessRain1 (2, 3), t' is a dummy variable which indicates 1 if rainfall in year t-1 is above the 110% (120%, 130%) of the average over the period 1970-2002. T-statistics are in brackets.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 7 Manufacturing output (Second-stage results)

	Dependent variable: Manufacturing output, t (in log growth)						
	GDP per capita < $10,000					GDP per capita < $4,000	GDP per capita > $10,000
	all		Upper hemisphere	Upper hemisphere*	Equator	Upper hemisphere	Upper hemisphere
	OLS (1)	IV (2)	IV (3)	IV (4)	IV (5)	IV (6)	IV (7)
Log yield growth, t-1	.08** [2.37]	.18** [2.04]	.19** [2.45]	.31*** [2.82]	.20 [1.20]	.23** [2.31]	.1.04 [.57]
Log yield growth, t	.08* [1.83]	-.08 [-.37]	.00 [.02]	.10 [.41]	-.17 [-.66]	-.03 [-.14]	-.14 [-.08]
Log exchange rate growth, t	-.16*** [-3.53]	-.16*** [-3.78]	-.19* [-1.74]	-.13 [-1.07]	-.20*** [-3.21]	-.14 [-.64]	-.70*** [-4.43]
R-squared	.17	.14	.18	.17	.15	.16	--
F-statistics (first-stage)	--	25.49	18.70	17.17	16.77	12.77	5.25
average GDP per capita	$3,708	$3,708	$4,006	$4,216	$2,950	$2,063	$22,053
Observations	1264	1264	627	448	691	356	626

Notes: Each observation is a country-year. 'Upper hemisphere (Upper 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. T-statistics are in brackets. *** p < 0.01, ** p < 0.05, * p < 0.1.

Table 8 Robustness Check (Second-stage results)

	Dependent variable: Manufacturing output, t (in log growth)							
	GDP per capita < $10,000 Upper-hemisphere countries							
	Using crop area weighted rainfall as instrument					Using non-crop area weighted rainfall as instrument		
	all	highly agricultural	low trade	high trade	low credit	all	highly agricultural	low trade
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log yield growth, t-1	.19**	.27*	.29**	-.06	.28***	.18	.05	.21
	[2.45]	[1.70]	[2.10]	[-.33]	[2.45]	[1.51]	[.21]	[1.22]
Log yield growth, t	.00	.13	.17	.21	.11	-.12	-.15	.06
	[.02]	[1.11]	[.70]	[1.32]	[.75]	[-.61]	[-.80]	[.37]
Log exchange rate growth, t	-.19*	-.35***	-.40***	-.22***	-.32***	-.19	-.34***	-.41***
	[-1.74]	[-2.81]	[-3.12]	[-3.23]	[-3.42]	[-1.61]	[-2.86]	[-3.31]
R-squared	.18	.37	.27	.31	.23	.10	.30	.26
F-statistics (first-stage)	21.47	16.06	24.38	9.46	25.61	16.12	9.25	18.24
average GDP per capita	$4,006	$2,354	$3,472	$4,929	$4,287	$3,898	$2,297	$3,412
Observations	627	247	376	199	380	612	244	362

Notes: Each observation is a country-year. All regressions (1)-(8) are performed over the upper-hemisphere countries (observations) whose latitude is greater than 10, and GDP per capita less than $10,000. ‘Highly agricultural’ represents observations with shares of agriculture production out of GDP greater than 20%. ‘Low (High) trade’ represents observations with export shares in manufacturing output less (greater) 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. T-statistics are in brackets. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 9 Employment in Manufacturing (Second-stage results)

	Dependent variable: Employment in Manufacturing (in log growth rates)							
	GDP per capita < $10,000					GDP per capita < $4,000		GDP per capita > $10,000
	Upper hemisphere			Upper hemisphere*	Equator	Upper hemisphere	Upper hemisphere*	Upper hemisphere
	OLS	IV	Low credit	IV	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log yield growth, t	.04**	.21***	.30***	.24***	-.09	.27***	.33***	.41
	[2.02]	[3.08]	[5.87]	[3.06]	[-.94]	[4.63]	[4.10]	[.20]
Log yield growth, t-1	.02	-.02	-.05	.02	.01	.00	.14	1.51
	[.75]	[-.33]	[-.51]	[.20]	[.16]	[.03]	[.81]	[.78]
Log exchange rate growth, t	-.03*	-.03*	-.01	-.04*	-.01	-.01	-.02	-.02
	[-1.86]	[-1.72]	[-.42]	[-1.91]	[-.70]	[-.27]	[-.43]	[-.22]
F-statistics (first-stage)	--	25.04	26.62	24.15	31.14	17.97	10.50	1.81
Observations	780	780	470	562	802	466	304	628

Notes: Each observation is a country-year. 'Upper hemisphere (Upper 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. T-statistics are in brackets. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 10 Sector-level Employment in Manufacturing (Second-stage results)

	Dependent variable: Employment in Manufacturing (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*	.08	.56***	.11	.20*	.36***	.00	.16
	[1.92]	[.85]	[3.85]	[.81]	[1.86]	[2.90]	[.02]	[.94]
Log yield growth, t-1	.16	-.09	-.09	-.05	.18	.14	-.13	.34
	[1.25]	[-.61]	[-.60]	[-.35]	[.98]	[.69]	[-.97]	[.73]
Log exchange rate growth, t	.04	.05	-.01	-.04	.02	.00	-.11*	.04
	[1.33]	[.87]	[-.24]	[-.80]	[.41]	[.07]	[-1.66]	[.51]
Observations	466	466	470	461	461	448	417	383

Notes: Each observation is a country-year. All regressions (1) – (8) are performed over the upper 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. T-statistics are in brackets. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 11 Capital Investment in Manufacturing (Second-stage results)

	Dependent variable: Capital investment in Manufacturing (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	IV	IV	IV	IV	IV
	(1)	(2)	(3)	(5)	(6)	(7)
Log yield growth, t-1	-.01	1.46**	1.22	1.62**	1.52**	.73
	[-.13]	[2.28]	[1.46]	[2.14]	[2.28]	[.62]
Log yield growth, t	-.10	1.17	3.55**	-.10	1.37*	-.76
	[-.84]	[1.62]	[2.52]	[-.14]	[1.83]	[-1.36]
Log exchange rate growth, t	-.27***	-.23***	-.16	-.40***	-.23***	-.1.06***
	[-3.62]	[-2.89]	[-1.21]	[-2.72]	[-2.93]	[-6.37]
F-statistics (first-stage)	--	10.54	4.76	5.07	10.72	3.52
Observations	763	763	386	400	865	513

Notes: 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. T-statistics are in brackets.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 12 Sector-level Capital Investment in Manufacturing (Second-stage results)

	Dependent variable: Capital Investment in Manufacturing (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	.10 [.17]	1.02 [1.34]	.04 [.06]	.81 [1.09]	1.39 [1.51]	1.91* [1.94]	.42 [.57]	1.11 [.92]
Log yield growth, t	-.34 [-.52]	1.56* [1.80]	-.23 [-.29]	.33 [.38]	1.75 [1.60]	1.34 [1.25]	1.61* [1.92]	1.27 [.83]
Log exchange rate growth, t	-.17** [-2.42]	-.18* [-1.90]	-.19** [-2.24]	-.13 [-1.37]	-.33*** [-2.91]	-.08 [-.74]	-.18* [-1.66]	-.10 [-.74]
Observations	743	736	749	726	722	738	645	626

Notes: Each observation is a country-year. All regressions (1) – (8) are performed over observations with GDP per capita less than $10,000. Each regression includes country and year fixed effects. T-statistics are in brackets.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 13 Domestic productivity shocks and crop prices (Second-stage results)

	Dependent variables (in log growth rates)						
	Wheat price	Wheat price	Maize price	Barley price	Soybean price	Sorghum price	Rice price
	OLS (1)	IV (2)	IV (3)	IV (4)	IV (5)	IV (6)	IV (7)
Log yield growth, t	-.16*** [-3.66]	-.86*** [-2.69]	-.78** [-2.32]	-.85*** [-2.64]	-.13 [-.51]	-1.29** [-2.23]	.33 [-.99]
Log yield growth, t-1	-.10** [-2.52]	-.74** [-1.96]	-.65 [-1.41]	-.72 [-1.61]	-.49*** [-3.74]	-1.17** [-2.09]	-.33 [-1.55]
Observations	1157	1140	1400	1057	732	718	1039

Notes: 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 results hold similarly when the sample is restricted with the $10,000 income cut. Each regression includes country and year fixed effects. Robust standard errors are clustered by country. T-statistics are in brackets.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 14 Two-country model
(A 15% decrease in agricultural productivity in Home country)

Foreign country size C	Changes in Home country equilibrium		
	$\%\Delta L^{*}_{a,H}$	$\%\Delta L^{*}_{m,H}$	$\%\Delta q^{*}_{m,H}$
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 Foreign country relative to Home country (e.g., $C = 0.01$ means that the size of foreign country is 1% of Home country size).

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), we can express both p_a and K_m in terms of L_m as follows:

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

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

Using the market clearing condition and Equations (A.1) - (A.4), we 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. 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, we notice 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 we assume 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 $(1-\beta_m)$ fraction of $(1-\alpha) \cdot I$ is spent on labor in manufacturing. Similarly, $(1-\beta_a)$ fraction 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, we notice 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, 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 $\sigma \to 1$.

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

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

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

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

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 I 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 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 decreasing income effects. Note that the elasticity for 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 a U-shape 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 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.

[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 thirty three 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.

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 good, 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, we can express $L_{m,F}$ in terms of $L_{m,H}$ as follows:

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

We also use the market clearing condition for the world market. That is, for each sector, the sum of produced quantity in the world equals the sum of the demand in the world, 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 we assume a small open economy where the price is fixed at the world price, $p_a = p_w$. Since prices are fixed, the demand system has no effect on output, so the resource allocations and manufacturing output are entirely determined by the supply side. Thus, we consider only the production side to obtain equilibrium solutions of our 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, we have

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

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

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

B Implications on Aggregate TFP

The main 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 counter-intuitive, as resources are moving toward the sector with declining productivity. How would such a reallocation pattern affect aggregate TFP? Meanwhile, we also have 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.4), 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.4). In both cases, the base price is country specific and is set at the equilibrium price obtained under 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 effect) are the same under the baseline model and under 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 under the small open economy.[5] For example, in Ethiopia, aggregate TFP decreases by 14% under the closed economy, while it decreases only by 7% under the small open economy. How does the same 15% decrease in agricultural productivity result in a larger reduction in aggregate productivity under 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 effect (between-sector effect) that 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,

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

[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.

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

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 $K^\beta L^{1-\beta}$, we 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 as it fits well to the context of the theory. Equation (B.4) can be thought 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 reallocated, thus initial sector shares being 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, we 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 its productivity or with 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.4 reports the decompositions of aggregate TFP growth in response to a 15% decrease in agricultural productivity. There are two dimensions in comparing 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, thus the share effects being negative (column 3 of Table A.4). For example, in Ethiopia, the share effect is -2.2% under the closed economy. On the other hand, the share effect under the small open economy is +4.1% (column 6). In short, the country could have done better by more than 6%, if it were 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.4). 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 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 unit of manufacturing good is needed to produce 1 unit of X, where p_x is given outside the model. Since manufacturing good 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 select $\beta_1 = 0.4$ 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 I 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 and reduces manufacturing output. This effect decreases with income levels, thus higher output fluctuations in poor countries. Importantly, like the baseline model results, the new model results show that there exist significant differences 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

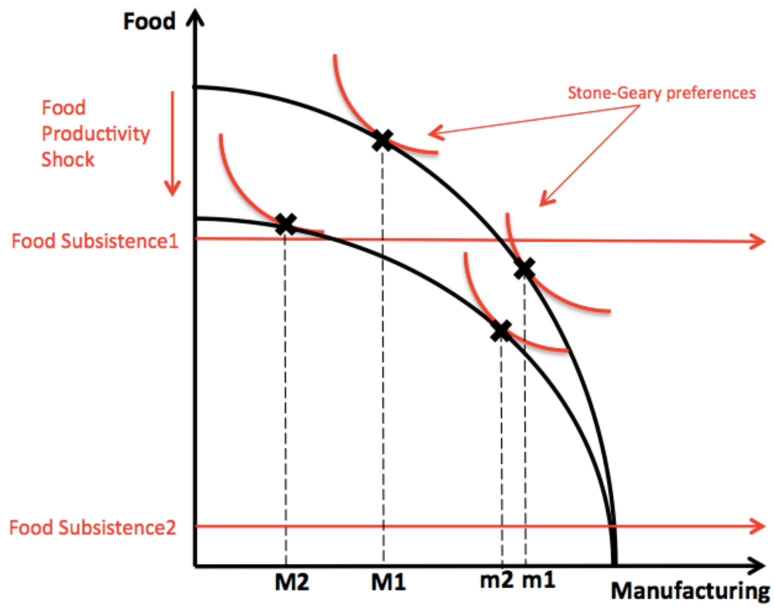

Figure A.1 Changes in equilibrium quantities in response to a negative shock to agricultural productivity

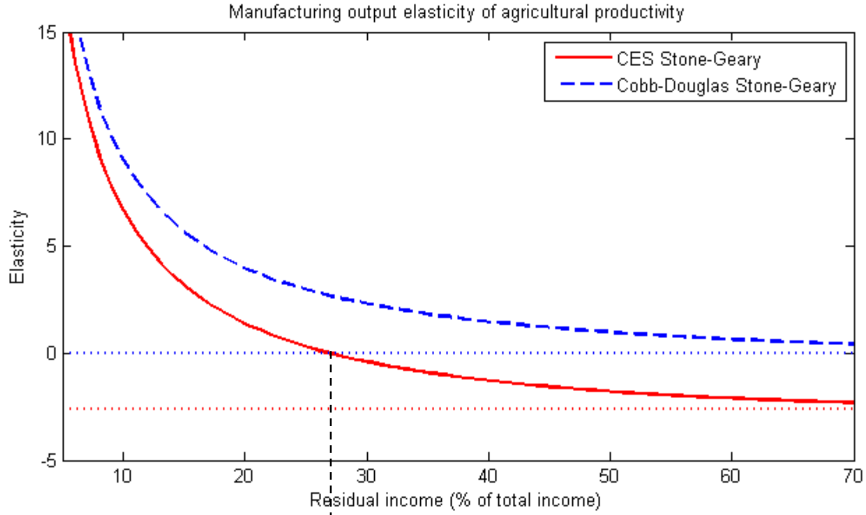

Figure A.2. Elasticity of manufacturing output with respect to agricultural productivity, against residual income (% of total income)

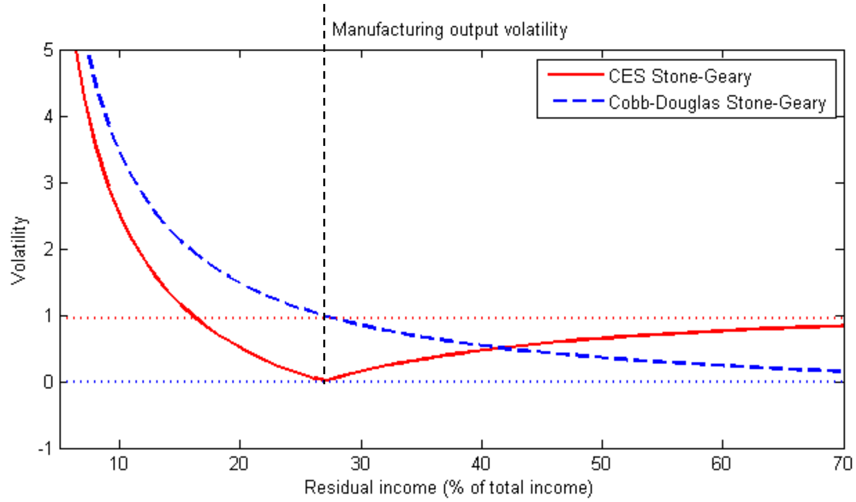

Figure A.3. Manufacturing output volatility against residual income (% of total income)

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

	Dependent variables	
	Manufacturing output volatility	Aggregate output volatility
Log GDP	-.03*** (.005)	-.007*** (.002)
Log population	-.006 (.005)	-.006*** (.001)
Constant	.44*** (.07)	.16*** (.03)
Adj R-squared	0.15	0.21
Observations	96	96

Note - OLS estimation results. Standard errors are in parenthesis. 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 annual growth rates are filtered by the HP(100) filter to control for time trends of growth rates. 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 opticalinstruments
8	Motor vehicles, trailers, semi-trailers; Other transport equipment

Table A.3. Standard deviations of the predicted manufacturing output growth rates
(based on the IV result on column 2, Table 7)

Countries	Volatility of predicted manuf. output (%)	(Data) Manuf. output volatility (%)	Predicted/Data
India	1.0	9.9	0.10
Morocco	2.3	16.4	0.14
Egypt	3.5	17.9	0.19
Romania	1.9	16.9	0.11
Portugal (~1977)	2.3	8.4	0.27
Developing countries* (Average values)	1.8	16.6	0.11

Notes: Volatility in percentage terms can be understood simply as the standard deviation of growth rates in percentage. Column 1 shows volatility values of predicted output based on the IV result on column 4 in Table 6. Volatility values in column 2 are computed directly from the data over the same sample (annual growth rates are filtered by HP(100) filter). Column 3 values are obtained from column 1 values divided by column 2 values. Developing countries* represent the observations associated with the regression result of the column 4 in Table 6.

Table A.4. Decompositions of changes in aggregate TFP
(A 15% decrease in agricultural productivity)

Country	Baseline model			Small open economy model		
	Productivity effect	Share effect	%ΔTFP	Productivity effect	Share effect	%ΔTFP
Ethiopia	- 11.3%	- 2.2%	- 13.5%	- 11.3%	+ 4.1%	- 7.2%
Ghana	- 7.5%	- 1.4%	- 8.9%	- 7.5%	+ 4.3%	- 3.2%
Malawi	- 7.3%	- 1.3%	- 8.7%	- 7.3%	+ 4.3%	- 3.1%
India	- 3.6%	- .6%	- 4.2%	-3.9%	+ 3.0%	- .9%
Bangladesh	- 3.4%	- .6%	- 4.0%	-3.7%	+ 2.9%	- .8%
Portugal	- 1.8%	- .3%	- 2.1%	-2%	+ 1.8%	- .2%
United States	- 0.8%	- .1%	- .9%	- .97%	+ .92%	- .05%

Table A.5 Aggregate output (second-stage results)

	Dependent variable: Aggregate GDP (in log growth rates)					
			Large Agriculture	Low Credit	Low Trade	High Trade
	OLS (1)	IV (2)	IV (3)	IV (4)	IV (5)	IV (6)
Log yield growth, t-1	.02 (.01)	.07** (.03)	.20*** (.06)	.09*** (.03)	.13*** (.05)	.02 (.06)
Log yield growth, t	.07*** (.01)	.10*** (.03)	.13** (.06)	.14*** (.03)	.15*** (.05)	.06 (.06)
Log exchange rate growth, t	-.02*** (.01)	-.02*** (.01)	-.01 (.01)	-.02** (.01)	-.04** (.02)	-.02 (.01)
Country fixed effects	yes	yes	yes	yes	yes	yes
Time fixed effects	yes	yes	yes	yes	yes	yes
R-squared	0.19	0.10	0.17	0.14	0.30	0.40
Observations	2375	2370	901	1202	757	525

Notes: Each observation is a country-year. Standard errors, in parenthesis, allow for clustering within a country. All samples in each regression are restricted to countries with sufficiently high agriculture share (higher than 10% out of total GDP). In regression (3), samples are restricted by agriculture share larger than 30%. 'Low credit' indicates the sample with private credit (% of total GDP) less than 20%. 'High (Low) trade' indicates the sample with export share in manufacturing output greater (less) than 20%.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A. 6 Rainfall and crop yields (First-stage results, 1960-2008)

	Dependent variable: Log growth in crop yield,t				
	Per capita GDP (PGDP) < $10,000			$10,000 < PGDP	
	(1)	(2)	(3)	(4)	(5)
Log rainfall growth, t	.30***	.30***	.31***	.02	.02
	(.06)	(.06)	(.05)	(.05)	(.05)
Tropical region × Log rainfall growth,t	-.24***	-.24***	-.24***	-.01	.00
	(.06)	(.06)	(.06)	(.05)	(.05)
Excess rain,t × Log rainfall growth,t			-.03		
			(.06)		
Log rainfall growth,t-1	.02	.04	.04	.05	.06
	(.03)	(.03)	(.03)	(.06)	(.06)
Tropical region × Log rainfall growth,t-1	-.00	-.03	-.03	-.10	-.06
	(.04)	(.04)	(.04)	(.08)	(.08)
Country fixed effects	no	yes	yes	no	yes
Time fixed effects	no	yes	yes	no	yes
R-Squared	.06	.09	.09	.00	.06
F-statistics	62.48	62.48	50.19	1.15	1.15
Observations	3848	3848	3848	1448	1448

Notes: Each observation is a country-year. Standard errors, in parenthesis, allow for clustering within a country. PGDP stands for per capita GDP (in 2005 international dollars). 'Excess rain, t' is a dummy variable which indicates 1 if rainfall in year t-1 is above the average over the period 1961-2008.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.7 Manufacturing output (Second-stage results, 1960-2008)

	Dependent variable: Manufacturing output, t (in log growth)						
	Per capita GDP < $10,000						
	All		Agriculture > 10%				
					Low trade	High trade	Low credit
	OLS	IV	IV	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log yield growth, t-1	.04*	.17*	.23**	.21*	.27***	.06	.48***
	(.02)	(.10)	(.09)	(.11)	(.08)	(.23)	(.13)
Log yield growth, t	.05	-.04	.05	.04	.06	-.24	.12
	(.04)	(.14)	(.10)	(.10)	(.10)	(.26)	(.16)
Log exchange rate growth, t	-.20***	-.20***	-.34***	-.31***	-.31***	-.24***	-.57***
	(.05)	(.05)	(.10)	(.09)	(.09)	(.05)	(.12)
Country fixed effects	yes	yes	yes	yes	yes	yes	yes
Time fixed effects	no	no	no	yes	yes	yes	yes
R-squared	0.12	0.11	0.15	0.19	0.38	0.28	0.19
Observations	1837	1817	1167	1167	404	636	776

Notes: Each observation is a country-year. Standard errors, in parenthesis, allow for clustering within a country. Regressions (3)-(7) are performed over the sample with agriculture shares (in total GDP) greater than 10%. Aggregate manufacturing output is in value added and excludes the sectors that use agricultural products as primary inputs. The samples here are all restricted by the per capita GDP less than $10,000 (in 2005 international dollars). 'Low credit' indicates the sample with private credit (% of total GDP) less than 30%. 'High (Low) trade' indicates the sample with export shares in manufacturing output greater (less) than 10%.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.8 Manufacturing output (Second-stage results, 1960-2008) II

	Dependent variable: Manufacturing output, t (in log growth)				
	PGDP < \$4,000			PGDP > \$10,000	
	IV	IV (Using crop-area weighted rainfall shocks)	IV (Using non-crop area rainfall shocks)	OLS	IV
	(1)	(2)	(3)	(4)	(5)
Log yield growth, t-1	.23**	.24**	.17	.01	3.51
	(.11)	(.11)	(.11)	(.03)	(4.46)
Log yield growth, t	.06	.04	.06	.17	1.02
	(.10)	(.11)	(.12)	(.10)	(3.26)
Log exchange rate growth, t	-.33***	-.34***	-.33***	-.57***	-.63**
	(.09)	(.12)	(.12)	(.19)	(.30)
Country fixed effects	yes	yes	yes	yes	yes
Time fixed effects	yes	yes	yes	no	no
R-squared	0.19	0.19	0.20	0.28	--
Observations	889	865	847	1132	1106

Notes: Each observation is a country-year. Standard errors, in parenthesis, allow for clustering within a country. Regressions (1)-(3) are performed over the sample with agriculture shares (in total GDP) greater than 10%. Regressions (2) and (3) use crop-area weighted rainfall and non-crop area rainfall as instruments instead of the simple area-weighted rainfall. PGDP stands for per capita GDP (in 2005 international dollars). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.9 Capital investments in manufacturing (Second-stage results, 1960-2008)

	Dependent variable: Manufacturing gross fixed capital formation (in log growth)				
	PGDP < $10,000				PGDP > $10,000
			Low trade	High trade	
	OLS	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)
Log yield growth, t-1	-.08	1.09*	1.43	.24	.15
	(.09)	(.63)	(1.26)	(.52)	(.58)
Log yield growth, t	-.10	.55	1.80***	-.83	-.19
	(.11)	(.75)	(.69)	(.80)	(.31)
Log exchange rate growth, t	-.28**	-.26**	-.17**	-.02	-.44
	(.12)	(.12)	(.07)	(.45)	(.24)
Country fixed effects	yes	yes	no	yes	yes
Time fixed effects	yes	yes	no	yes	yes
R-squared	.10	--	--	.23	0.22
Observations	1085	1073	670	258	946

Notes: Each observation is a country-year. Standard errors, in parenthesis, allow for clustering within a country. 'High (Low) trade' indicates the sample with export shares in manufacturing output greater (less) than 30%. PGDP stands for per capita GDP (in 2005 international dollars). *** p < 0.01, ** p < 0.05, * p < 0.1.

Table A.10 Manufacturing employment (Second-stage results, 1960-2008)

	Dependent variable: Manufacturing employment (in log growth rates) PGDP < $10,000				
	Upper hemisphere				Equator
			PGDP < $4,000	PGDP > $10,000	
	OLS	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)
Log yield growth, t-1	.00	-.06	-.05	.27	.27
	(.02)	(.05)	(.07)	(.58)	(.47)
Log yield growth, t	.02	.12**	.19**	.16	-.53
	(.02)	(.06)	(.08)	(.39)	(.68)
Log exchange rate growth, t	-.04**	-.04**	-.02	-.01	.01
	(.02)	(.02)	(.03)	(.04)	(.03)
Country fixed effects	yes	yes	yes	yes	yes
Time fixed effects	yes	yes	yes	yes	yes
R-squared	0.17	0.12	0.09	--	--
Observations	1139	1119	651	1019	567

Notes: Each observation is a country-year. Standard errors, in parenthesis, allow for clustering within a country. 'Upper hemisphere (Equator)' indicates the countries that are above 10-degree latitude (between -10 and 10 degree latitudes). PGDP stands for per capita GDP (in 2005 international dollars).
*** p < 0.01, ** p < 0.05, * p < 0.1.

Table A.11 List of Countries

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