Agricultural Risk, Intermediate Inputs, and Cross-Country Productivity Differences*

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Abstract

Agricultural productivity is crucial for understanding aggregate cross-country income differences. This paper considers the impact of low intermediate input intensity in developing countries. In a dynamic general equilibrium model with idiosyncratic shocks, incomplete markets, and subsistence requirements, farmers in developing countries rationally use fewer intermediate inputs because it limits their exposure to uninsurable shocks. The calibrated model accounts for nearly half of the difference in intermediate shares between the U.S. and India and amplifies differences in per capita GDP by twenty percent relative to an identical model with perfect insurance.

JEL Classification Codes: O11, O41

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1 Introduction

Differences in agricultural labor productivity between the richest and poorest countries are twice as large as differences in aggregate labor productivity. In spite of this, the least developed countries in the world employ over eighty percent of their population in the agricultural sector. Since these countries employ such a large fraction of their population in a particularly unproductive sector, development accounting suggests that understanding agricultural productivity differences are crucial for understanding aggregate differences.[1]

One possible cause of agricultural productivity differences is that farmers in developing countries use fewer intermediate inputs. For example, as a share of harvest value, the value of intermediate inputs used on farms ranges from 4 percent in Uganda to 40 percent in the United States. Moreover, I document in Section 2 that this positive cross-country correlation does not exist in other sectors, suggesting that it may be an important margin for understanding why the agricultural sector exhibits significantly lower labor productivity than the nonagricultural sector in developing countries. The goal of this paper is to provide a theory to understand the cross-country correlation between the agricultural intermediate input share and per capita income, and in turn, quantitatively assess its role for cross-country productivity differences.

In this paper, low intermediate input intensity is generated endogenously as a response to low total factor productivity (TFP). Because intermediate decisions are made before the realization of productivity shocks, the absence of insurance markets requires farmers to internalize the impact this choice will have on *ex post* consumption. In particular, purchasing more intermediate inputs leads to lower consumption in the event of a low shock realization. The extent to which this consideration impacts the *ex ante* intermediate choice depends critically on the income level of farmers. Low shock realizations are

[1] This argument has been made in various forms starting with Restuccia et al. (2008), and also Caselli (2005), Vollrath (2009), and Gollin et al. (2014), among others.

particularly disastrous for farmers in extremely poor countries, since consumption moves close to subsistence. These farmers are less willing to take on the risk associated with intermediate inputs usage, thus driving down labor productivity in developing countries.

I formalize and quantify this idea with a dynamic general equilibrium model in which both aggregate and sector-specific differences can potentially influence farmer response to shocks. Farmers produce agricultural output utilizing intermediate inputs, and are subject to incomplete markets and random fluctuations in farm productivity. In this sense, the model is similar to those used to focus on capital misallocation with self-insurance (e.g. Buera et al., 2011; Midrigan and Xu, 2014; Moll, 2014, among others). Here, however, deviations from unconstrained profit maximization are driven not by explicit input market frictions, but instead by the inability to insure *ex post* consumption. The timing of input choices implies that each shock realizations is weighted its risk neutral probability which includes a normalized measure of marginal utility. As TFP decreases in poor countries, income moves closer to subsistence and marginal utility at low shock realizations increases, so that farmers in poor countries put relatively more weight on bad potential outcomes. From the perspective of misallocation (e.g. Restuccia and Rogerson, 2008; Hsieh and Klenow, 2009), this implies a wedge between the expected profit-maximizing marginal value and price of intermediate inputs, and is in fact isomorphic to a tax wedge in a model with no risk.

The result depends critically on the inclusion of a subsistence requirement when the equilibrium price of agricultural output varies across countries. I show that without subsistence, uninsurable shocks play no role in understanding differences in the agricultural input mix nor aggregate productivity across countries. That is, the agricultural productivity gap between any two economies is identical regardless of insurance against farm-level shocks. The addition of the subsistence requirement then has two important implications. First, I show theoretically that it generates a positive correlation between the intermediate share and aggregate income consistent with the empirical evidence in Section 2. Second, identical distortions have differential impacts in rich and poor countries when combined with this risk channel. In this sense, the model with subsistence provides an otherwise absent complementary amplification channel for distortions considered within a complete markets framework, including transportation costs (Adamopoulos, 2011; Gollin and Rogerson, 2014), the link from distortions to farm size (Adamopoulos and Restuccia, 2014) or technology choice (Yang and Zhu, 2013), or more general distortions that affect input markets (Gollin et al., 2004; Restuccia et al., 2008).

I then turn to quantify the cross-country impact of this theory. I calibrate the model using a mix of aggregate and micro-level data from India, where the nominal intermediate input share in agriculture is 11 percent. I jointly match consumption and production volatility to allow for some consumption smoothing in the model, and I also include relevant sector-neutral and agriculture-specific features to isolate the importance of each. I then vary exogenous sector-neutral productivity and the cost of intermediate inputs to U.S. levels. Since these differences exogenously increase labor productivity, I isolate the impact of the theory developed here by asking how much larger productivity differences are relative to an identical model in which shocks are perfectly insured.

The quantitative results imply that the seemingly sub-optimal intermediate input choices in agriculture can be partially explained as a rational responses by farmers to risk, and through that distortion, affect aggregate labor productivity across countries. The calibrated model predicts that the Indian economy has an intermediate input share of 0.26, compared to the U.S. intermediate share of 0.40. This is 48 percent of the difference found in the data. This risk-driven distortion then amplifies cross-country productivity differences relative to a model with perfectly insured shocks. Agricultural productivity differences increase by 30 percent from a factor of 34.5 to 45.0, while GDP per capita differences increase from a factor of 6.4 to 7.8 for an amplification of 22 percent. Risk, therefore, plays an important role in understanding both agricultural input mix and productivity across countries.

This paper contributes to a recent macroeconomic literature on the role of agriculture in understanding cross-country income differences, including Gollin et al. (2004), Lagakos and Waugh (2013), Adamopoulos and Restuccia (2014), Herrendorf and Schoellman (2015), and Tombe (2015). Mostly closely related is the work of Restuccia et al. (2008), who also focus on the role of intermediate inputs. Building off their work, this paper contributes a micro-founded rationale for distortions in the intermediate input market by focusing on the risk associated with intermediate input choices. Moreover, I show that the distortions emphasized in their work have a larger impact when combined with risk, and can help explain resource misallocation in agriculture. In this sense, the paper more broadly relates to the literature relating establishment-level distortions to aggregate productivity (Restuccia and Rogerson, 2008; Hsieh and Klenow, 2009). While recent work has focused on the role of financial development to explain pervasive deviations from undistorted profit maximizing behavior (e.g. Buera et al., 2011; Midrigan and Xu, 2014; Moll, 2014), uninsurable risk has the potential to similarly distort input choices when combined with a subsistence requirement. The paper is therefore also similar to Angeletos (2007), who shows that the increase in savings relative to a complete markets benchmark in Aiyagari (1994)-style models is reversed when one considered capital income instead of labor income.

2 Motivating Evidence

Define the real intermediate input share as $X^{j*} := p_x^* X^j / p_a^* Y_a^j$, where X^j is intermediate input consumption in agriculture of country j, Y_a^j is agricultural output, and p_x^* and p_a^* are international prices of intermediates and output. The nominal intermediate share is given by $\widehat{X}^j := p_x^j X^j / p_a^j Y_a^j$, where the only difference is that intermediates and output are valued at nominal country-specific prices p_x^j and p_a^j. As discussed in the introduction, the influential work of Restuccia et al. (2008) finds that real intermediate shares differ substantially across countries. Using data from Prasada Rao (1993), which is constructed from Food and Agricultural Organization (FAO) statistics and underlies the Restuccia et al. (2008) analysis, Figure 1a reproduces their finding of a strong positive correlation between GDP per capita and the real intermediate share. In addition to the correlation, the level differences are also large compared to other inputs. Merging this data with FAO estimates on capital stock in agriculture I find that the cross-country 90-10 ratio of intermediates per worker is more than double that of capital per worker in agriculture (Table 1). I then compute a simple variance decomposition in the style of Caselli (2005). Relative to capital per worker differences, variation in real intermediates per worker account for three times more of the variance in agricultural gross output per worker.

While differences in real shares drive productivity differences, differences in the nominal shares identify distortions. Figures 1b uses the same data and plots the nominal share. Again, there is a strong positive correlation of 0.65. The tenth percentile country, as ranked by GDP per capita, has a nominal intermediate share that is one-fourth of the intermediate share in the United States.[2] The positive correlation with per capita GDP in both

[2] If rich countries are producing different crops than developing countries, one might suspect that the result is driven by different production techniques for these different types of output. While I cannot directly test this, I do group countries by latitude to control for the type of agricultural production, and compare within-group variation. The same correlation holds within groups.

real and nominally priced shares implies that the price ratio p_x/p_a does not systematically vary with development, though there is substantial variation in the price ratio, as Figure 1c shows.

2.1 Evidence from Micro Data

I next turn to evidence from micro data. I use the Living Standard Measurement Studies (LSMS) released by the World Bank in cooperation with local governments. I include all countries with surveys after 2000, staying as close to 2010 as possible. There are 14 countries with sufficient data that, combined with weights in the data, provide nationally representative samples in each country.

I first compute the nominal expenditure share of fertilizer and pesticides to corroborate aggregate statistics.[3] I use the median sale price to value harvest quantities in countries where the nominal expenditures are not directly available. Since the data is nationally representative when combined with available weights, aggregating gives the national expenditure shares. Figure 2 combines this data with Penn World Table GDP per capita, and confirms the positive relationship.

2.1.1 The Role of Risk

Is there a relationship between input use and agricultural risk in the data? I examine this using available data on rainfall variability, an exogenous source of agricultural risk across regions within an available set of sub-Saharan African countries for which I have LSMS data.[4]

[3]Other intermediate inputs, such as fuel, are only available in some countries so I exclude them here. Also, note that these are not consumption shares. Fertilizer and pesticide consumption is only available in 6 of the countries. Since I focus on inorganic fertilizer and pesticide (i.e. not manure) nominal expenditures and consumption valued at market prices should be similar.

[4]Comparable cross-country data on agricultural inputs and outputs combined with standard measures of household risk such as consumption volatility do not exist. Consumption volatility is nonetheless an endogenous measure, reflecting both inherent risk and risk coping measures such as intermediate choices. Moreover, the within country variation I use has the added advantage of keeping other relevant economic variables, such as the price of intermediates, relatively constant.

Rainfall data comes from the Tropical Rainfall Measuring Mission (TRMM), available from the Goddard Earth Sciences Data and Information Services Center administered by the U.S. National Aeronautics and Space Administration (NASA), and is a U.S.-Japan collaboration on satellite monitoring of world-wide precipitation. It provides monthly rainfall estimates (1998 - 2014) for the entire non-arctic world ($[-50, 50] \times [-180, 180]$ latitude-longitude) on 0.25×0.25 degree cells, for a total of 576,000 cells. I use this data to create historical rainfall variation (weather risk) for each cell during the country-specific main cropping season defined in the LSMS documentation. I then merge this information with household GPS coordinates available in some of the LSMS countries. Since the rainfall data begins in January 1998, I restrict attention to the subset of countries with data after 2005. The restrictions of (1) post-2005 data and (2) GPS coordinates leaves four of the original fourteen countries: Malawi, Niger, Tanzania, and Uganda. The 0.25×0.25 degree grid is fine enough to enough to allow substantial variation within each country. The Malawi LSMS has households contained in 144 unique TRMM cells, Niger has 129, Tanzania has 223, and Uganda has 171.

To assess the impact of risk on intermediate expenditures, I run the regression

$$y_{ir} = \alpha + \beta\sigma_{ir}^{rain} + \gamma Save_{ir} + \theta(\sigma_{ir}^{rain} \times Save_{ir}) + \eta X_{ir} + \varepsilon_{ir} \tag{2.1}$$

where i is household and r is region. The dependent variable y_{ir} takes two forms. First is expenditures on fertilizer and pesticide (plus one to allow for zeros) and the second is the expenditure share relative to harvest value. Both are normalized by regional means. On the right hand side, σ_{ir}^{rain} is historical standard deviation of rainfall from 1998 to the year before the survey, $Save_{ir}$ is the value of livestock holdings one year earlier normalized by regional mean, and X_{ir} is a set of controls.[5] I use livestock holdings for two reasons. First, they are an important part of savings used to smooth consumption (e.g. Rosenzweig and Wolpin, 1993). Second, the LSMS asks about livestock holdings one year prior to the survey, which sidesteps concerns about conflating pre-harvest savings and post-harvest responses. Livestock is the only savings vehicle with this question, hence its use in lieu of a broader notion of savings.

Tables 2 and 3 present the results for log expenditures and expenditure shares respectively. In all cases, estimated coefficient is less than zero and is significant for all countries except Uganda.[6] Households who face larger weather risk across all four countries spend less on fertilizer and pesticide and have lower expenditure shares of harvest value, consistent with the idea of risk playing an important role determining intermediate shares. The interaction term is positive across all specifications, consistent with the idea that risk is less of a problem for richer households, but is imprecisely estimated. This is driven by the fact that relatively little variation in livestock holdings. In Malawi and Uganda for example, the median value of livestock is zero. In Niger, where the twenty-fifth percentile of livestock value is positive, the interaction term is positive and significant.

These results complement a growing micro literature on the importance of risk for agricultural investment across a large set of developing countries. Dercon and Christiaensen (2011) show downside consumption risk depresses fertilizer use in Ethiopia by reconstructing potential consumption realizations from panel data. Emerick et al. (2015) provide experimental evidence that decreased downside risk through the introduction of new flood tolerance rice increases fertilizer investment in India. Further experimental evidence from the introduction of rainfall insurance shows that insurance can incentivize farmers

[5] Controls include number of adult men, adult women, and children in the household, household head gender, education, age, squared age, historical average rainy season rainfall, and squared and cubed terms of $Save_{ir}$

[6] The (unweighted) total expenditure share of harvest value in Uganda is 0.004 and only 360 of 2139 observations have positive expenditures, which explains why the estimates are less precise.

to take more risk across a variety of countries (Mobarak and Rosenzweig, 2012; Cole et al., 2013b; Cai et al., 2014; Karlan et al., 2014).[7] Taken together, the results suggest risk is an important constraint to intermediate input use across the developing world.

2.2 Comparison to Manufacturing and Services

As a last step, I turn back to aggregate data to compare intermediate input shares across sectors using the United Nations *System of National Accounts* (SNA). The U.N. data includes 87 countries in which data is sufficiently complete to construct nominal intermediate shares across the broadly defined sectors of agriculture, manufacturing, and services. These nominal intermediate shares are plotted for in Figure 3, along with the nonagricultural sector measured as the total economy net of agriculture. Figure 3a confirms the relationship between the agricultural intermediate input share and per capita GDP. Figures 3c and 3d, however, show the intermediate input shares in manufacturing and services exhibit no such relationship. The figures also include the estimated coefficients from the simple linear regression of the sectoral intermediate share on log PPP GDP per capita. Only agriculture has a slope significantly different from zero, implying that the positive relationship between the intermediate input share and per capita income is unique to the agricultural sector.

The rest of this paper is devoted to developing and quantifying a model to understand the cause of the correlation in agriculture and assess its impact on cross-country productivity differences.

[7] There is also a growing literature on the difficulty in designing the proper insurance contract in these settings, including issues of trust, basis risk, and limited understanding. See for example Mobarak and Rosenzweig (2012), Cole et al. (2013a), and Karlan et al. (2014).

3 Model

Time is discrete, and a model period is one year. There are two sectors, sector a for agriculture and sector m for manufacturing, which includes all nonagriculture. The manufacturing good is the numeraire, so its output price is normalized to $p_{mt} = 1$ for all t. Within an economy, decisions are made by a measure one of infinitely-lived households.

3.1 Technology

Manufacturing The manufacturing output good can be used as either consumption or as intermediate inputs in agricultural production. Production is characterized by a stand-in firm which uses only labor services N_{mt} to produce output according to the constant returns to scale production function $Y_{mt} = AN_{mt}$ where A is a sector neutral TFP parameter. The parameter A is country-specific, and is a measure of the overall productivity of the economy. The firm maximizes profits at each date t, so that N_{mt} is the solution to

$$\max_{N_{mt} \geq 0} \; AN_{mt} - w_t N_{mt} \tag{3.1}$$

where w_t is the wage paid per unit of N_{mt}. In a competitive equilibrium $w_t = A$ for all t.

Agriculture Each household is endowed with one farm that requires intermediate inputs x and labor n_a. Production occurs according to the decreasing returns to scale production function $y_{at} = z_t A x_t^{\psi} n_{at}^{\eta}$, where $\psi + \eta < 1$ and A is, again, sector neutral TFP.[8] The shock z_t is a household-specific productivity shock drawn from a time-invariant distribution with cumulative distribution

[8] Alternatively, one could assume land is normalized to $l = 1$ and inelastically supplied. In principal, this eliminates land as margin for adjustment. *Ex post* adjustment of land is unlikely given the non-existent or limited land markets in poor countries.

function $Q(z)$ and support on $[\underline{z}, \overline{z}]$.[9,10] The realization of z_t is i.i.d. with respect to both households and time. I assume the law of large numbers holds, so that the distribution of shocks across households is certain. Intermediate inputs are purchased from the manufacturing sector, at the price $p_x \geq 1$, which varies across countries. Note that the implicit assumption made is that there exists a technology to turn one unit of manufacturing output into $1/p_x$ units of intermediate input. This is a simple way to capture the fact that intermediate inputs are more expensive in developing countries.

3.2 Household Utility and Decisions

A household values consumption from both sectors a and m, and maximizes expected utility $\mathbb{E}_0 \left[\sum_{t=0}^{\infty} \beta^t u(c_{at}, c_{mt})\right]$ with discount factor $\beta \in (0, 1)$. The period t utility flow takes the form $u(c_{at}, c_{mt}) = \alpha \log(c_{at} - \bar{a}) + (1 - \alpha) \log(c_{mt})$, where c_{jt} is consumption from sector $j \in \{a, m\}$ and $\bar{a} > 0$ is the subsistence requirement of agricultural consumption. The utility function is consistent with the structural transformation paths when households consume gross output (Herrendorf et al., 2013).

Households do not have access to insurance markets, so that the shock can only be insured against through self-insurance. To this end, they save by storing agricultural output. This storage depreciates at a country-specific rate δ to capture differences in agricultural savings technologies across countries.

3.2.1 Decision Timing

At time $t - 1$, households save b_t units of the agricultural good. A fraction δ depreciates, and the household enters time t with $(1 - \delta)b_t$ units of savings.

[9] Throughout, it is assumed $\underline{z}$ is high enough to guarantee subsistence can be satisfied for all economies with TFP A in some set $\mathcal{A} \subset \mathbb{R}_+$. The results should be interpreted as holding for economies with TFP in the set $\mathcal{A}$.

[10] Note that increased intermediate intensity does not decrease the variance of shocks. This is supported by micro evidence in both developed and developing countries (Just and Pope, 1979; Traxler et al., 1995).

The period t decision problem is broken down into two stages denoted *ordering* and *production*, which are separated by the realization of the shock z.

In the ordering stage, each household chooses intermediates x_t to use in their farm. After ordering, z_t is realized. All production and consumption occurs in the production stage. First, a household chooses how to allocate labor between the agricultural sector, where they can work on the household farm, and in the manufacturing sector, where they can work for wage w_t which is taxed at rate $\tau \geq 0$. Note that this allows labor to be used to smooth consumption across shock realizations. A fraction ν of the tax revenue is rebated back to households as a lump-sum transfer $T(b, z)$, while the fraction $1 - \nu$ is used to purchase manufacturing output and discarded. After labor is decided, all production takes place. There is a centralized market for buying and selling goods, implying a unique equilibrium price p_a. Profits are made, all factors of production are paid, and consumption and savings choices $(c_{at}, c_{mt}, b_{t+1})$ take place.[11]

3.3 Recursive Problem

The timing described above implies that the household state variable is savings b, and the aggregate state is the distribution of savings across all households, denoted $\mu(b)$. Since I will be primarily studying the stationary equilibrium, I suppress the dependence of the decision problem on the aggregate state $\mu(b)$.

At the production stage, once the choice of x is made and z realized, the value of entering time t with $(1 - \delta)b$ savings is

$$v^p(x, b, z) = \max_{c_a, c_m, n_a, b'} \quad \alpha \log(c_a - \bar{a}) + (1 - \alpha) \log(c_m) + \beta v^o(b') \tag{3.2}$$

[11] I abstract from manufacturing risk here because manufacturing households are significantly richer. As I show in Section 6, the impact of risk is small at sufficiently high levels of savings.

subject to constraint set

$$p_a c_a + c_m + p_a b' = p_a z A x^{\psi} n_a^{\eta} - p_x x + (1-\tau) w (1-n_a) + p_a (1-\delta) b + T(b,z)$$
$$b' \geq 0, \qquad c_a \geq \bar{a}, \qquad c_m \geq 0$$

where v^o is the value of entering the ordering stage at $t+1$ with b' units of savings in the stationary equilibrium. The production problem in (3.2) defines decision rules as a function of the intermediate choice. Working backwards, the ordering stage value of entering time t with b savings is

$$v^o(b) = \max_{x \geq 0} \quad \int_z v^p(x,b,z) dQ(z). \tag{3.3}$$

This defines the decision rule for intermediate inputs $x(b)$ and therefore the production stage decision rules $c_a(b,z)$, $c_m(b,z)$, $n_a(b,z)$, and $b'(b,z)$.

3.4 Stationary Equilibrium

The stationary competitive equilibrium of this economy is defined by an invariant distribution $\mu = \mu^*$, a value function v^o, decision rules x, n_a, b', c_a, c_m, labor choice N_m, prices p_a and w, and a transfer function $T(b,z)$ such that (1) the value function v^o solves the households's problem given by (3.2) and (3.3) with the associated decision rules, (2) N_m solves the sector m firm problem (3.1), (3) the state contingent transfer balances for all (b,z): $\nu\tau A(1-n_a(b,z)) = T(b,z)$, (4) the law of motion for μ, denoted $\Lambda(\mu)$, is such that $\Lambda(\mu^*) = \mu^*$, and μ^* is consistent with $Q(z)$ and decision rules, and (5) markets clear:

(a) Manufacturing labor market:

$$N_m = 1 - \int_z \int_b n_a(b,z) d\mu dQ(z)$$

(b) Agricultural consumption market:

$$\int_b \int_z c_a(b,z)dQ(z)d\mu + \delta \int_b b d\mu = \int_b \int_z zAx(b)^{\psi} n_a(b,z)^{\eta} dQ(z)d\mu$$

(c) Manufacturing consumption market:

$$\int_b \int_z c_m(b,z)dQ(z)d\mu + p_x \int_b x(b)d\mu + (1-\nu)\tau A \int_b (1-n_a(b,z))dQ(z)d\mu = AN_m$$

4 Characterization and Analytic Results

To clarify the mechanics of the model, this section analytically characterizes some of the main model predictions. In particular, I show that the interaction of uninsured shocks and subsistence requirements generate a positive correlation between TFP and the nominal intermediate share. To highlight TFP specifically, I assume throughout this section that $p_x = 1$ and $\tau = 0$ in all economies, though none of the results rely on this assumption. I further consider the static version of the model (identically, $\delta = 1$ for all economies). All proofs are relegated to Appendix D.

Given total consumption expenditure $C := p_a c_a + c_m$, the optimal allocation between agricultural and manufacturing consumption is given by $c_a(C) = \bar{a} + (\alpha/p_a)(C - p_a\bar{a})$ and $c_m(C) = (1-\alpha)(C - p_a\bar{a})$. Using these decision rules, the utility flow can be rewritten as a function of total expenditures C, $\widetilde{u}(C) = \Omega - \alpha\log(p_a) + \log(C - p_a\bar{a})$, where Ω is a constant. This reduces the problem to solving just the input choices x and $n_a(z)$. A variance decomposition of the intermediate input first order condition yields

$$\frac{\psi}{\int_Z z^{1/(1-\eta)} A p_a^{1/(1-\eta)} F'(x) dQ(z)} - 1 = -cov\left(\frac{\widetilde{u}'(C(x,z))}{\mathbb{E}_z[\widetilde{u}'(C(x,z))]}, z^{1/(1-\eta)} A p_a^{1/(1-\eta)} F'(x)\right) \tag{4.1}$$

where $F(x)$ is the production function after solving for optimal labor $n_a(z)$. The lefthand side of (4.1) is the percentage change in the nominal intermediate share by moving from incomplete to complete markets. This immediately implies that the nominal intermediate share in all countries will be less that ψ, as the covariance between the risk neutral weights and the marginal return to intermediates is negative when shocks are uninsurable. Morduch (1995) refers to this result as "income smoothing," as households shift away from risky input choices to smooth consumption across states of the world, and is the broad motivation behind the agricultural insurance initiatives cited in Section 2.1. However, Proposition 1 shows that the appeal to risk aversion and incomplete markets alone is not sufficient to generate excess income smoothing in poor economies when the price of agriculture varies across economies.

Proposition 1. *If $\bar{a} = 0$, (1) the nominal intermediate share is independent of TFP, (2) the share of labor in agriculture is independent of TFP, and (3) for two economies with TFP levels A^1 and A^2, the agricultural output per worker difference between the two economies is the same regardless of whether or not markets are complete. That is, denoting Y_a^{ij} and N_a^{ij} as agricultural output and employment in economy $i \in \{1, 2\}$ with market structure $j \in \{C, I\}$ (complete and incomplete),*

$$\frac{Y_a^{1C}/N_a^{1C}}{Y_a^{2C}/N_a^{2C}} = \frac{Y_a^{1I}/N_a^{1I}}{Y_a^{2I}/N_a^{2I}}.$$

Despite the fact that consumption risk lowers the nominal intermediate share relative to its profit-maximizing level, it remains constant across countries when $\bar{a} = 0$. The key here is relative risk aversion. Since the utility function $\widetilde{u}$ is defined over aggregate consumption expenditures C, relative risk aversion can also be defined over C, and is given by $C/(C - p_a\bar{a})$. When $\bar{a} = 0$, households exhibit constant relative risk aversion. The equilibrium price therefore adjusts in response to low TFP and offsets the cost of consumption risk. Proposition 2 shows that the inclusion of subsistence requirements – and therefore the change from constant to decreasing relative risk aversion – breaks this result, and can qualitatively replicate the empirical correlation between the nominal intermediate share and income from Section 2.

Proposition 2. *In the competitive equilibrium, the nominal intermediate share is increasing in A if and only if $\bar{a} > 0$.*

The same non-homothenticity that generates income effects in structural transformation (and therefore the negative relationship between agricultural labor and TFP in the model) also implies a positive relationship between the intermediate share and aggregate income. I show in the appendix that the risk-based wedge between the marginal value and price of intermediate inputs is isomorphic to a reduced form tax wedge on intermediate inputs in the corresponding model that abstracts from risky production.

5 Calibration and Testing Model Predictions

Since the model predicts that uninsured shocks both depress intermediate intensity and act as a distortion in developing countries, I turn to quantifying the impact on cross-country productivity differences. I begin by calibrating the model to India using a combination of micro and aggregate statistics. I then vary agriculture-specific distortions (p_x, τ, δ) and sector-neutral TFP A to create a U.S. model economy to assess the impact of agricultural risk on intermediate shares and labor productivity across countries. The exogenous differences fed into the model generate labor productivity differences across the two countries, so I isolate the impact of risk by comparing the model predictions against an identical model with complete insurance against shocks.

I calibrate the model with the ICRISAT Village Level Studies (VLS2) data from India. The ICRISAT VLS2 is a household-level survey on in India starting in 2001 and running through 2013, and is a continuation of earlier ICRISAT data from 1975-1984. The VLS2 includes information household composition, consumption, farm inputs, and harvest values, and includes both a cross-sectional and panel component. Consumption data is not collected in 2007, so I focus on the 2001-2006 panel.

Since rainfall is a key component of risk in the developing world, I first compute the coefficient of variation of annual rainfall to see whether the ICRISAT villages are a reasonable approximation for India. I do so using the same rainfall data in Section 2.1 for each of about 13,500 cells in India, from 1998-2005. The map of rainfall c.v. is in Figure 4a, while the density across cells is plotted in Figure 4b. The six ICRISAT villages are all very close to the mean, as 5 of 6 villages fall within 5 percent of the mean cell. The sixth, Shirapur, is somewhat higher at 25 percent above the mean cell.

The model includes ten parameters, six of which are common across the two economies, and four that determine the distortions facing India that do not exist in the United States. They are discussed in turn.

5.1 Common Parameters

The six common parameters are the production exponents ψ and η, the shock distribution, the rebate on taxes ν, and preference parameters $\bar{a}$, α, and β. I set $\alpha = 0.005$ following Restuccia et al. (2008) and Lagakos and Waugh (2013) and $\beta = 0.96$. I set $\bar{a} = 0.03$, so that the Indian model economy has 50 percent of the population engaged in agriculture in the stationary equilibrium, consistent with sectoral employment in India (World Bank, 2015).

That leaves the production parameters, shock distribution, and tax rebate. The production parameters cannot be set to match nominal factor shares in the Indian economy, as the realized shares combine both the technological parameters and the distortions I seek to investigate. Instead, I assume the technologies are the same across U.S. and India and choose $\eta = 0.40$ and $\psi = 0.40$ to be consistent with U.S. estimates. Note however that the model predicts that the nominal labor share should equal $\eta = 0.40$ in both the U.S.

and India. This is consistent with the ICRISAT data. ICRISAT includes both hired and household labor, valued at gender-specific market wages, which is the counterpart to the model definition. For each household (363 in 2006) I compute the value of labor services as a share of harvest value, and the average is 0.41. The same procedure for the nominal intermediate share implies a value of 0.11, much lower than the U.S. level, and consistent with substantial distortions in intermediate use in India.

The last two parameters are the variance of the shock distribution and tax rebate share ν. I choose these parameters to match the average standard deviation of growth rates in household-level harvest values and total consumption expenditures. For this, I use the six year panel of of households from 2001-2006, of which there are 236 across six villages with consumption, harvest, and household characteristics data available. However, the data includes variation in harvest and consumption due to heterogeneity in household size, education, and village-level variation that are not modeled here. To the extent that these are predictable, directly using variance in the data would attribute them to unanticipated shocks. Instead I follow Kaboski and Townsend (2011) and others and purge the data of these factors with the regressions

$$\begin{aligned}\log(Y_{ivt}) &= \alpha^Y + \beta^Y X_{ivt} + \theta^Y_{vt} + \varepsilon^Y_{ivt} \\ \log(C_{ivt}) &= \alpha^C + \beta^C X_{ivt} + \theta^C_{vt} + \varepsilon^C_{ivt}\end{aligned}$$

where θ_{vt} is a village-time fixed effect, and X_{ivt} is a set of controls for household i at time t that include number of men, women, and children, and age, gender, and education of the household head. Y and C are the household values of harvest and consumption, deflated by the Indian consumer price index. The R^2 on these regressions are 0.33 and 0.74 respectively, so that these features account for a large part of the variation, especially for consumption. I then compute the sample average for the vector X_{ivt}, denoted $\overline{X}_{ivt}$, and compute the new data as

$$\widehat{\log(Y_{ivt})} = \widehat{\alpha}^Y + \widehat{\beta}^Y \overline{X}_{ivt} + \widehat{\varepsilon}^Y_{ivt} \tag{5.1}$$

$$\widehat{\log(C_{ivt})} = \widehat{\alpha}^C + \widehat{\beta}^C \overline{X}_{ivt} + \widehat{\varepsilon}^C_{ivt}. \tag{5.2}$$

My measure of the growth of harvest and consumption are then the differences $\Delta Y_{ivt} = \widehat{\log(Y_{ivt})} - \widehat{\log(Y_{ivt-1})}$ and $\Delta C_{ivt} = \widehat{\log(C_{ivt})} - \widehat{\log(C_{ivt-1})}$. The estimated harvest growth rates are more volatile than consumption, consistent with the ability of households to partially smooth income shocks. The average standard deviation of harvest growth across households is $\sigma_{\Delta Y} = 1.00$ compared to $\sigma_{\Delta C} = 0.49$ for consumption. Matching these two standard deviations imply a standard deviation of the shock distribution of $\sigma_z = 0.48$ and $\nu = 0.085$. That is, 8.5 percent of tax revenue is rebated to households. While the averages are targeted, Figures 5a and 5b plot the density of harvest and consumption growth rate volatility in both the model and the data to assess whether the distributions match with the data. I compute the implied volatility in the model by simulating 100,000 individuals for six years each, consistent with the ICRISAT panel length. Both implied distributions fit the data well despite not being targeted directly.

5.2 Economy Specific Parameters

There are four dimensions along which India will differ from the U.S. economy: TFP A, the depreciation rate δ, the tax rate τ, and the intermediate input price p_x. I use TFP and p_x numbers from Restuccia et al. (2008). This implies $(A^{India}, p_x^{India}) = (0.22, 2.77)$ and normalized values $(A^{US}, p_x^{US}) = (1, 1)$.

The last two parameters, τ and δ, control the relevance of the two smoothing channels in the model. First, τ is the ease by which households can smooth consumption by moving labor across sectors in response to shocks. I set $\tau^{US} = 0$, and calibrate τ^{India} from the ICRISAT data. ICRISAT includes household hours and earnings at wage jobs in both the agricultural and nonagricultural sector. I compute the wage in sector s as

$$w^s = \frac{\sum_i e_i^s}{\sum_i h_i^s} \quad \text{for } s \in \{a, m\}$$

where e_i is earnings in sector s for household i, and h_i^s is total hours worked in sector s. The distortion is $\tau = 1 - w^a/w^m$. The ICRISAT data in 2006 imply $\tau^{India} = 0.57$.

The depreciation rate of savings δ determines the availability of smoothing through storing agricultural output. Udry (1995), Fafchamps et al. (1998), and Kazianga and Udry (2006) all point to the importance of crop storage for smoothing consumption in the developing world. There is also evidence that livestock is used to smooth consumption, particularly in India (e.g. Rosenzweig and Wolpin, 1993). I therefore use the total value of livestock holdings and crop storage as the measure of savings, both of which are available in ICRISAT. In 2006, 54 percent of savings in the average ICRISAT household is livestock, while the other 46 percent comes from stored crops, suggesting both are important.[12] The total market value of livestock and stored crops is 96 percent of total harvest value in the average household, and I set $\delta^{India} = 0.15$ to match this fact. This is consistent with large costs to storage in developing countries. Despite targeting only the average, Figure 5c shows that the savings distribution in the model matches the data well. I set $\delta^{US} = 0$, but this has no impact on the results as the U.S. model economy is sufficiently rich that the savings distribution at any negative interest rate is nearly degenerate at zero.

[12] ICRISAT also includes the pesticide and fertilizer storage. Consistent with the model used here, there is almost no storage of either. Including these intermediates in savings, only 0.6 percent of savings in the average household is made up of pesticide and fertilizer. Only 8 percent of households store any fertilizer or pesticide.

5.3 Savings, Consumption, and Intermediate Use: Model vs. Data

With the calibrated model in hand, I lastly assess model predictions for the relationship between consumption volatility, savings, and intermediate intensity by comparing the Indian model predictions to ICRISAT data. These are out-of-sample tests designed to assess whether the key model predictions are operational in the data. To compute the regressions in the model, I simulate 100,000 households in the Indian stationary equilibrium. I then compute standard errors using a bootstrap procedure to create 1000 samples of 205 households, consistent with the number of households in ICRISAT with the full six year panel and the requisite data.[13]

The results are broken into two sections. The first relates to the relationship between savings and intermediate use. The model predicts that the *ex ante* intermediate choice and farm yield are positively related to savings, as households can better insure low shock realizations. The second covers the relationship between consumption volatility and intermediate use. Here, the model predicts a positive relationship between intermediate inputs and the coefficient of variation of consumption. I test both sets of of predictions, and find that the same relationships hold in the data.

5.3.1 Savings and Intermediate Intensity

I consider the relationship between savings and intermediate use with the regressions

$$x_{2006} = \alpha + \beta b_{2005} + \varepsilon \tag{5.3}$$

$$\left(\frac{p_x x}{p_a y_a}\right)_{2006} = \alpha + \beta b_{2005} + \varepsilon \tag{5.4}$$

$$yield_{2006} = \alpha + \beta b_{2005} + \varepsilon \tag{5.5}$$

[13] 31 households are missing data on fertilizer use, hence the decrease in sample size from the the 236 used in Section 5.1. Redoing the analysis exclusively with this smaller sample does not change the results.

where savings is lagged to prevent endogeneity concerns. In all regressions, both dependent and independent variables are normalized by their respective means. Results are presented in Table 4.

First, regression (5.3) shows that the model and data match well when considering the *ex ante* intermediate choice, where $\widehat{\beta}^{data} = 0.37$ and $\widehat{\beta}^{model} = 0.39$. Both are significant at one percent. In contrast, the *ex post* nominal shares are partially driven by unexpected volatility in output. Correspondingly, the R^2 in model regression (5.4) decreases from 0.53 to 0.02 in the model and from 0.17 to 0.00 in the data. Moreover, the estimate of $\widehat{\beta}^{data} = 0.01$ is small and statistically insignificant. The model prediction is somewhat stronger, with $\widehat{\beta}^{model} = 0.09$. This estimate is significant at ten percent, but no stricter, despite the strong relationship between the *ex ante* choice and savings.

Lastly, regression (5.5) considers the relationship between farm yield, measured as harvest value per acre, and lagged savings. Both the model and the data predict a strong positive relationship. The model estimate is $\widehat{\beta}^{model} = 0.26$, somewhat larger than the data estimate $\widehat{\beta}^{data} = 0.11$, but both are significant at one percent. These positive estimates occur despite the fact that using yield as the dependent variable suffers from the same *ex post* issue as using the realized intermediate share, evidenced by the relatively low R^2 estimates in both the model and the data regressions. To rationalize the different predictions of these two regressions, note that the *ex post* nominal intermediate share and farm yield in the model are

$$\begin{aligned}
\frac{p_x x}{p_a y_a(x,z)} &= p_x z^{\frac{-1}{1-\eta}} x^{\frac{1-\eta-\psi}{1-\eta}} (p_a A)^{\frac{-1}{1-\eta}} \left(\frac{\eta}{w}\right)^{\frac{-\eta}{1-\eta}} \\
p_a y_a(x,z) &= z^{\frac{1}{1-\eta}} x^{\frac{\psi}{1-\eta}} (p_a A)^{\frac{1}{1-\eta}} \left(\frac{\eta}{w}\right)^{\frac{\eta}{1-\eta}}.
\end{aligned}$$

The calibrated model implies $(1-\eta-\psi)/(1-\eta) = 0.33$ and $\psi/(1-\eta) = 0.67$. The increased relevance of variation in x when considering yield, which regression (5.3) shows is tightly related to variation in b, allows for a statistically significant estimate of savings on yield.

5.3.2 Consumption Volatility and Intermediate Intensity

I next turn to the relationship between consumption volatility and intermediate use. In both the model and the data, I ask the relationship between the coefficient of variation of consumption and average intermediate use during the six year panel. That is, denoting $\widehat{x}_{it}$ as the realized nominal intermediate share of household i at time t, I run the regression

$$\frac{\sum_{t=2001}^{t=2006} \widehat{x}_{it}}{6} = \alpha + \beta \left(\frac{\sigma^C}{\mu^C} \right)_i + \varepsilon_i, \tag{5.6}$$

The preferred comparison is the consumption estimates from regression (5.2), in which $C_{it} = \exp(\widehat{\log(C_{ivt})})$, for the reasons discussed in Section 5.1. For completeness, I also report results the household consumption directly from ICRISAT (deflated by the Indian CPI). The results are in Table 5. The model is consistent with the positive relationship between the consumption coefficient of variation and the average intermediate share found in the data, in which the model predicts $\widehat{\beta}^{model} = 0.09$, compared to $\widehat{\beta}^{est-data} = 0.15$ using the estimated consumption data.

The key intuition for this result is the positive correlation between the standard deviation and mean of consumption across households, in which the model also matches the data. The model predicts a correlation of 0.88, compared to 0.85 using the consumption data estimated from (5.2) and 0.90 using the direct ICRISAT consumption data. Given the strong positive correlation in the model, the results from regression (5.6) imply that an increase in mean consumption must be met with a less than one-for-one increase in the standard deviation of consumption. That is, the regression

$$\mu_i^C = \alpha + \beta \sigma_i^C + \varepsilon_i \tag{5.7}$$

implies an estimate of $\widehat{\beta}^{model} \in (0,1)$ in the model. Table 6 shows the result of this regression in the model and compares it to the data. The model matches the estimated data well with $\widehat{\beta}^{model} = 0.22$ and $\widehat{\beta}^{est-data} = 0.28$, though the unmodified consumption data predicts a higher estimate $\widehat{\beta}^{data} = 0.66$.

The model predictions are consistent with the empirical household-level relationship between intermediate input usage, savings, and consumption volatility. In the next section I therefore proceed to assess the quantitative cross-country implications of the model tested here.

6 Quantitative Cross-Country Results

The main cross-country results on productivity and input mix are in Table 7. First, note that the U.S. model economy is sufficiently rich that the move from complete to incomplete markets has little impact. The nominal intermediate share and employment share remain nearly identical.

This is not the case in India. The elimination of complete markets causes the nominal intermediate share in India to drop from 0.40 to 0.26. The model therefore captures 48 percent of the nominal intermediate share difference between the U.S. and India.[14] This causes agriculture to become more labor intensive in India, as the employment share in agriculture increases by 47 percent relative to its complete markets counterpart. The change in input mix is driven by an increase in household-level misallocation. Figure 6a plots the ratio $\phi^{risk}(b) := \psi / \mathbb{E}_z[\widehat{x}(b)]$, where $\mathbb{E}_z[\widehat{x}(b)]$ is the expected nominal intermediate

[14] An alternative exercise is to lower exogenous agricultural productivity until the predicted real intermediate share differences matched the data. Targeting this moment directly implies a productivity too low to satisfy subsistence among the households who receive the lowest shock realization while holding no savings.

share for a household with savings b, in both the U.S. and Indian economies.[15] The implied household-level distortion is higher in the Indian economy, particularly among the poorest. Thus, risk distorts the efficient distribution of intermediate inputs across production units, in the style of Restuccia and Rogerson (2008) or Hsieh and Klenow (2009).

The increased labor intensity in Indian agriculture then impacts productivity in both agriculture (measured as the U.S.–India ratio of agricultural gross output per worker) and in the aggregate (U.S. priced GDP per capita). The agricultural productivity gap the two countries increases by 32 percent from 34.2 to 45.3, while the aggregate gap increases by 22 percent from 6.4 to 7.8. Thus, the introduction of risk provides a substantial amplification of cross-country productivity differences at both the agricultural and aggregate level.

I next turn to understanding the underlying forces generating the amplification. There are two: a direct decrease in the real intermediate share driven by an unwillingness to take risk, and a general equilibrium effect as the price p_a adjusts in response. I decompose the importance of these two effects in Table 8. First, the complete markets model requires p_x to increase from $p_x = 2.77$ to $p_x = 3.70$ (34 percent) to match the real intermediate share predicted in the incomplete markets Indian economy. This is the direct effect of risk relative to a complete markets model such as Restuccia et al. (2008). This direct effect implies a 15 percent increase in agricultural employment and a 14 percent decrease in agricultural productivity.

Despite the identical real intermediate shares, the model developed here predicts a larger change in agricultural employment ($N_a = 0.40$ to $N_a = 0.50$), which is driven by the larger increase in the agricultural price ($p_a = 3.14$ to $p_a = 3.52$). This excess increase is the additional general equilibrium effect of

[15] This ratio is the risk-generated household-level wedge required in a model in which the intermediate choice is made after the realization of the shock, and thus measures intermediate input misallocation in the model. See Appendix A for the complete formulation of this result.

incomplete markets. Comparing rows two and three of the table, 58 percent of the change in agricultural productivity in the Indian model economy comes from the direct effect of a drop in the real intermediate share. The other 42 percent comes from the fact that generating the drop in the real intermediate share requires a higher price, and thus a larger shift of employment toward agriculture. Fifty-five percent of the increase in p_a is due to this direct effect, while the other 45 percent is the larger general equilibrium response of the incomplete markets model.

How reasonable is this general equilibrium effect? The model predicts $(p_x^{India}/p_a^{India})/(p_x^{USA}/p_a^{USA}) = 0.66$. The statistics in Restuccia et al. (2008) derived from Prasada Rao (1993) imply a value of 0.55, so the model actually somewhat underpredicts the gap. Looking back on Figure 1c, which plots the relationship between the price ratio p_x/p_a relative to the U.S., the relatively strict 90 percent confidence interval around regression line includes the value 0.66 for India. The amplification predicted by the model is therefore well within reason of variation in the data.[16]

7 Heterogenous Impact of Agricultural Distortions

As can be seen in Figure 6a, the model predicts substantial variation in the implied household-level distortion. I next turn to assessing how variation in agricultural distortions change this underlying household-level misallocation. I do so by varying p_x from $p_x = 2.77$ to $p_x = 1$ in both the Indian and U.S. model economies. This price plays an important role in a number of recent theories of agricultural productivity, including those that rely on agriculture-specific input market distortions (Gollin et al., 2004; Restuccia et al., 2008), internal trade and transportation costs (Adamopoulos, 2011; Gollin and Rogerson, 2014),

[16] This general equilibrium effect also implies that the aggregate increase in income from a large-scale insurance program is larger than would be expected from a partial equilibrium result. This is in contrast to Buera et al. (2014), who find that the general equilibrium effects of microfinance dampen the partial equilibrium effect on income.

and those that link intermediate prices to technology choice (Yang and Zhu, 2013).

The main results are in Table 9. The results show that the impact on productivity depends critically on the level of overall initial productivity in the economy, which is contrast to theories such as Restuccia and Rogerson (2008) and Hsieh and Klenow (2009). Agricultural productivity increases by 98 percent in India compared to 65 percent in the United States (Table 9). This is driven by differential responses to the underlying household distortion. As can be see in Figure 6b, it drops by as much as 60 percent among the poorest households in India compared to negligible changes in the U.S..

Table 10 decomposes the productivity changes into the two effects discussed in Section 6. Changes in the real intermediate share play only a small role. As highlighted in Restuccia et al. (2008), the decrease in p_x causes both countries to increase their real intermediate shares. However, while there is a slightly larger increase in India, the impact is similar across countries. The real intermediate share increases by 70 percent in the U.S. and 74 percent in India. The change in sectoral labor is more stark. While agricultural employment drops by 34 percent in the U.S., it drops by 52 percent in India.[17]

To further understand the impact of a change in the distortion p_x, Figure 7 shows the dynamics of the response of the baseline Indian economy to a surprise decrease in p_x from 2.77 to 1.00. The model reaches its new steady state relatively quickly. In doing so, the agricultural aggregates all overshoot their steady state levels. Initially when $p_x = 1$, households are saving too much and thus are willing to take on more risk, as evidenced by the sharp increase in the nominal intermediate share. Savings is a costly activity here, so there is a balance between savings and consumption. As such, savings

[17] The lack of variation in cross-country real intermediate share changes is due the same equilibrium forces that generate the large change in sectoral employment. Intuitively, when p_x decreases, Indian households are willing to take more risk *ceteris paribus*. However, the large drop in p_a – 94 percent in India – lowers the return to intermediates, and therefore dampens the effect. I detail this argument and provide a decomposition of this result in Appendix B.2.

continually drops in the economy, as the incentives to self-insure decrease as p_x decreases. As households dissave, the relative price, employment share, and nominal intermediate share all converge to the new steady state.

The results therefore show that the interaction of risk and subsistence requirements implies the effect of changing distortions is no longer independent of sector-neutral productivity, and moreover, provides a complimentary amplification channel for other theories considered in the literature.

8 Conclusion

This paper quantifies the role of idiosyncratic production risk in accounting for sectoral output per worker differences in a two sector general equilibrium model. In poor countries, farmers use fewer intermediate inputs, driving down agricultural productivity. The model provides a risk-based foundation for misallocation across agricultural production units, but the ability to generate relatively larger distortions in poor economies depends critically on the inclusion of a subsistence requirement. Quantitatively, the model captures half of the difference in intermediate input shares between the richest and poorest countries. This has important quantitative implications for productivity across countries. Relative to an identical model with complete insurance, the distortionary impact of risk amplifies agricultural productivity differences by about thirty percent and aggregate productivity differences by twenty percent.

The model also predicts that the impact of agricultural distortions depends critically on the overall level of productivity in the economy. Counterfactual experiments show that lowering these distortions can substantially decrease the household-level distortion that risk creates, but has a much larger effect in poor countries. This result is particularly important in light of the fact that the model captures about half of the difference in nominal intermediate shares, leaving room for complimentary explanations. Yang and Zhu (2013), for example, highlight technological choice in agriculture in which farmers can choose to use a technology with no intermediate inputs. A more detailed analysis of the the link between such theories will hopefully provide a more complete picture of agricultural input choices and productivity.

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9 Tables

Table 1: Agricultural Input Differences Across Countries (1985)

	90/10 Ratio	Variance decomposition ($\alpha_k = 0.30$, $\alpha_x = 0.50$)	Variance decomposition ($\alpha_k = 0.30$, $\alpha_x = 0.40$)
Output per worker	59.82	–	–
Capital per worker	82.78	0.11	0.11
Intermediate inputs per worker	196.38	0.38	0.26

Table notes: Data is from FAO and Prasada Rao (1993). The variance decomposition numbers are given by the following: $\frac{var(\log(k^{\alpha_k} x^{\alpha_x}))}{var(\log(y_a))}$ where each row shuts down the other input. For example, row two (capital) is measured by setting $\alpha_x = 0$, or $\frac{var(\log(k^{\alpha_k}))}{var(\log(y_a))}$.

Table 2: Intermediate expenditures and rainfall variation

Dependent variable: *log expenditures + 1*	Malawi	Niger	Tanzania	Uganda
σ^{rain}	-4.612***	-13.634***	-6.417**	-7.342
	(0.760)	(3.667)	(2.796)	(4.658)
Livestock (t-1)	0.056	-0.131	0.229	-0.665
	(0.066)	(0.178)	(0.077)	(0.229)
$\sigma^{rain} \times$ Livestock (t-1)	0.283	2.003	0.588	0.647
	(0.278)	(1.329)	(0.403)	(1.33)
Obs.	10,297	2132	2434	2118
R^2	0.074	0.064	0.274	0.094

Table notes: Robust standard errors are in parentheses. Significance at 0.01, 0.05, 0.1 levels denoted by ***, **, and *.

Table 3: Intermediate expenditures and rainfall variation

Dependent variable: *expenditure share*	Malawi	Niger	Tanzania	Uganda
σ^{rain}	-0.098***	-0.411*	-0.163***	-0.005
	(0.037)	(0.247)	(0.058)	(0.010)
Livestock (t-1)	-0.001	-0.009*	0.000	-0.000
	(0.002)	(0.005)	(0.001)	(0.003)
$\sigma^{rain} \times$ Livestock (t-1)	0.012	0.56*	0.003	0.003
	(0.009)	(0.029)	(0.005)	(0.003)
Obs.	9915	2132	2434	2118
R^2	0.027	0.0225	0.1938	0.083

Table notes: Robust standard errors are in parentheses. Significance at 0.01, 0.05, 0.1 levels denoted by ***, **, and *.

Table 4: Savings and Intermediate Inputs (Model vs. Data)

	Model	Data	Model	Data	Model	Data
Constant	0.632^{***}	0.610^{***}	0.855^{***}	0.992^{***}	0.741^{***}	0.892^{***}
	(0.045)	(0.112)	(0.095)	(0.088)	(0.094)	(0.071)
Savings	0.368^{***}	0.390^{***}	0.088^{*}	0.008	0.258^{***}	0.106^{***}
	(0.039)	(0.061)	(0.077)	(0.047)	(0.088)	(0.038)
R^2	0.532	0.168	0.020	0.000	0.057	0.020
Dependent variable	Expenditures	Expenditures	Nominal share	Nominal share	Yield	Yield

Table notes: Significance at 0.01, 0.05, 0.1 levels denoted by ***, **, and *. Yield is measured as total harvest revenue per acre of land. The model standard errors are bootstrapped using 1000 samples of 205 individuals. Dependent and independent variables are normalized by sample mean.

Table 5: Consumption Volatility and Intermediate Inputs (Model vs. Data)

	Model	Data (estimated)	Data (direct)
Constant	0.912^{***}	0.758^{***}	0.769^{***}
	(0.051)	(0.117)	(0.135)
c.v. of consumption	0.088^{*}	0.154^{**}	0.231^{*}
	(0.049)	(0.063)	(0.119)
Obs	205	205	205
R^2	0.020	0.029	0.018
Corr(σ_C, μ_C)	0.884^{***}	0.846^{***}	0.898^{***}

Table notes: Significance at 0.01, 0.05, 0.1 levels denoted by ***, **, and *. The model standard errors are bootstrapped using 1000 samples of 205 individuals. Column 2 computes consumption as the resulting estimates from regression (5.2). Column 3 computes household consumption directly from ICRISAT data, deflating by the Indian CPI. Dependent and independent variables are normalized by sample mean.

Table 6: Mean and Standard Deviation of Consumption (Model vs. Data)

	Model	Data (estimated)	Data (direct)
Constant	0.778^{***}	0.722^{***}	0.338^{***}
	(0.015)	(0.019)	(0.029)
σ^C	0.223^{***}	0.278^{***}	0.662^{***}
	(0.018)	(0.012)	(0.023)
Obs	205	205	205
R^2	0.781	0.715	0.805

Table notes: Significance at 0.01, 0.05, 0.1 levels denoted by ***, **, and *. The model standard errors are bootstrapped using 1000 samples of 205 individuals. Column 2 computes consumption as the resulting estimates from regression (5.2). Column 3 computes household consumption directly from ICRISAT data, deflating by the Indian CPI. Dependent and independent variables are normalized by sample mean.

Table 7: Uninsured Risk and Labor Productivity

	Labor Productivity Gap		p_xX/p_aY_a		N_a *(%)*	
Economy	Agriculture	Aggregate	Rich	Poor	Rich	Poor
Data: U.S./India	77.4	10.6	0.40	0.11	1.6	50.0
Data: 90/10 Ratio	63.7	23.1	0.40	0.09	2.0	82.0
Model with						
Incomplete markets	45.0	7.8	0.40	0.26	1.2	0.50
Complete markets	34.5	6.4	0.40	0.40	1.2	0.34

Table notes: The second row is the differences between the ninetieth and tenth percentile countries, while the first directly compares the U.S. and India. Results are presented for U.S. and Indian model economies with complete and incomplete markets.

Table 8: Decomposition of intermediate share changes

	X/Y	p_xX/p_aY_a	N_a	Y_a/N_a	p_a	p_x
Complete Markets (baseline)	1.00	1.00	1.00	1.00	1.00	1.00
Complete Markets ($p_x^{India} = 3.7$)	0.86	1.00	1.15	0.86	1.16	1.34
Incomplete Markets (baseline)	0.86	0.66	1.46	0.76	1.29	1.00

Table notes: All three rows are the Indian model economy. Rows one and three, labeled "baseline," each have $p_x = 2.77$. The second row sets $p_x = 3.7$ to match the real intermediate share in the incomplete markets economy. The first row is normalized to one.

Table 9: Agricultural productivity as p_x changes

	$A = 0.22$	$A = 1$
$p_x = 2.77$	0.023	0.607
$p_x = 1$	0.044	1.000
% increase	93.7	64.8

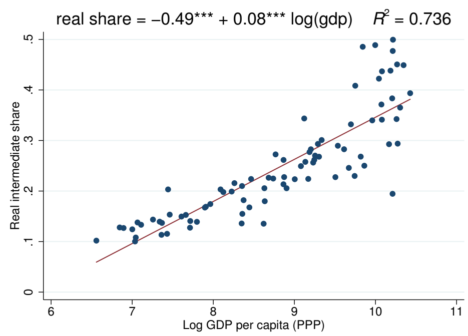
Table 10: Agricultural input changes as p_x changes

	$\frac{p_a X}{p_a Y_a}$	X/Y_a	N_a	p_a
$A = 1$				
$p_x = 2.77$	0.99	0.59	1.53	1.94
$p_x = 1$	1.00	1.00	1.00	1.00
$A = 0.22$				
$p_x = 2.77$	0.82	0.57	2.08	1.64
$p_x = 1$	1.00	1.00	1.00	1.00

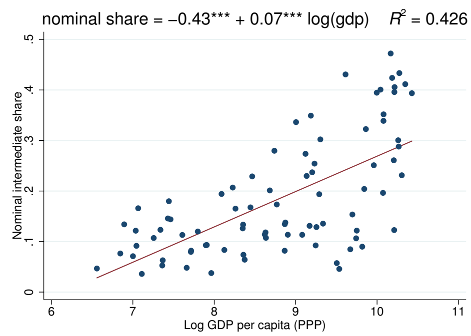
10 Figures

Figure 1: Cross-Country Intermediate Shares (1985)

(a) Real intermediate share



(b) Nominal intermediate share



(c) Nominal price ratio

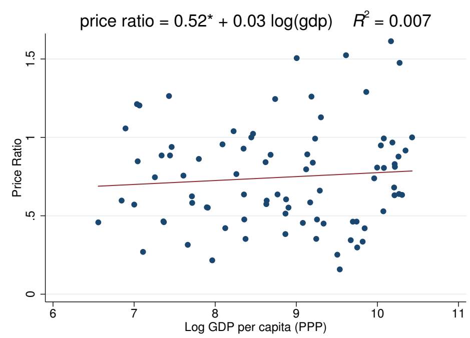


Figure notes: Significance of coefficient estimates at 0.01, 0.05, 0.1 levels denoted by ***, **, and *.

Figure 2: Nominal expenditure shares from LSMS micro data

(a) Fertilizer

(b) Fertilizer and Pesticide

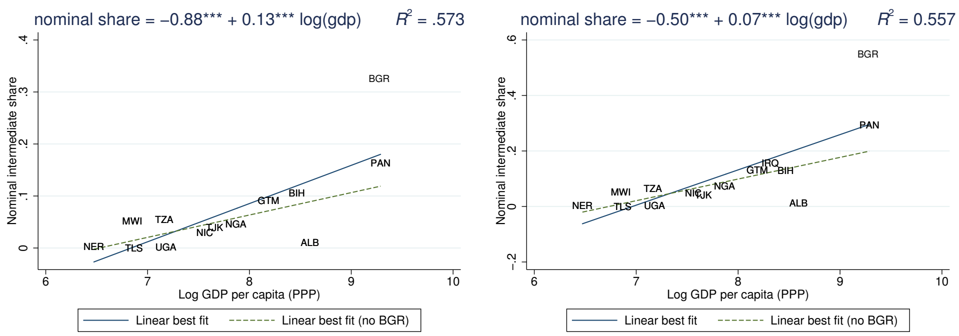
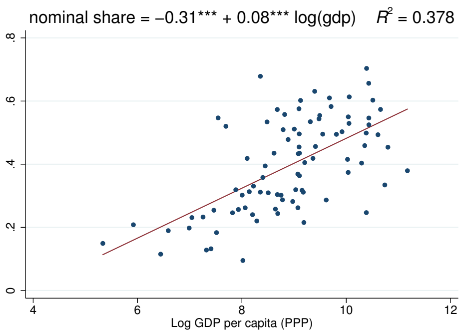


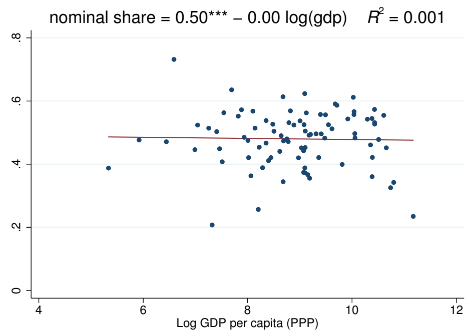
Figure notes: Presented regression results include all countries. Significance of coefficient estimates at 0.01, 0.05, 0.1 levels denoted by ***, **, and *. Excluding Bulgaria (BGR) still maintains the positive relationship at the one percent level.

Figure 3: Sectoral nominal intermediate shares (2005)

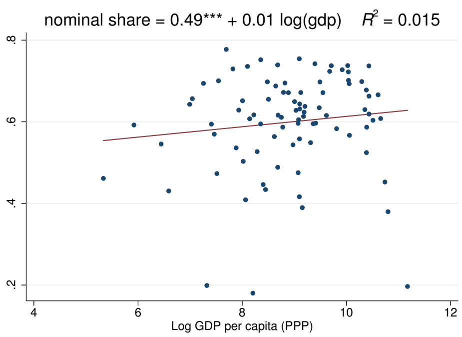
(a) Agriculture



(b) Non-Agriculture



(c) Manufacturing



(d) Services

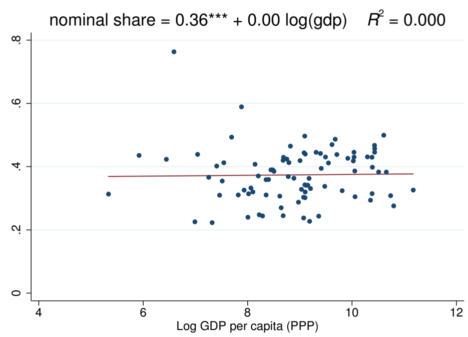
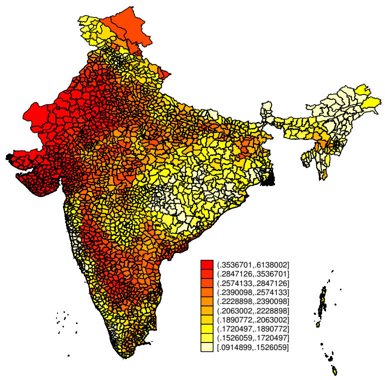


Figure notes: Non-agriculture is the entire economy net of the agriculture sector. Significance of coefficient estimates at 0.01, 0.05, 0.1 levels denoted by ***, **, and *.

Figure 4: Coefficient of Variation of Annual Rainfall in India

(a) Map



(b) Density

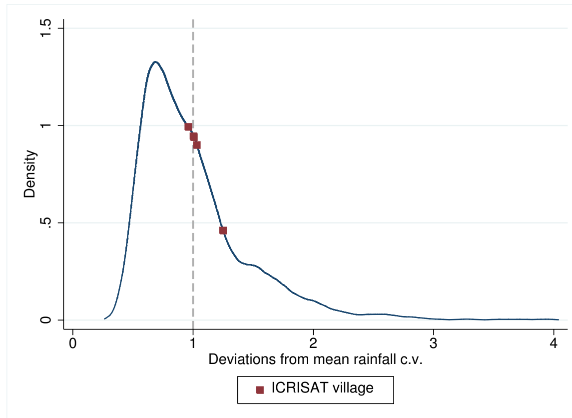
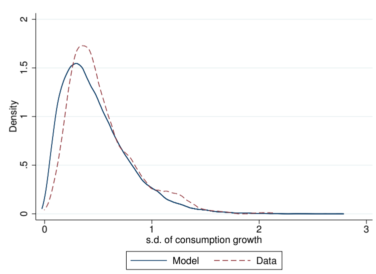
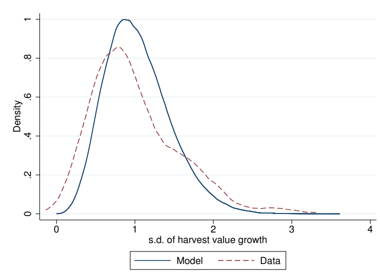


Figure 5: Fit of Model Distributions

(a) Consumption Growth Volatility



(b) Harvest Growth Volatility



(c) Savings Rate

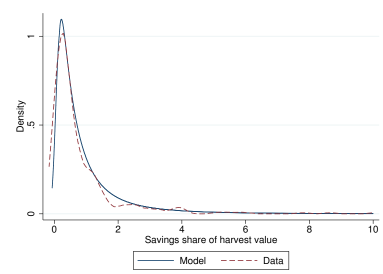
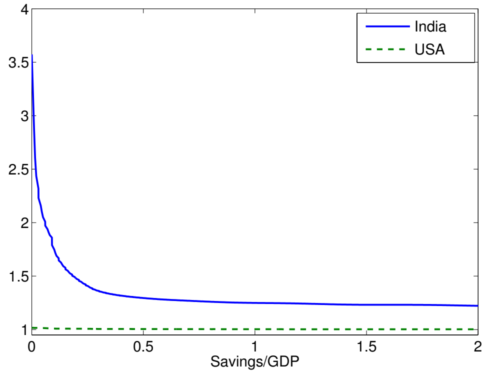


Figure 6: Household level distortion $\phi^{risk}(b)$

(a) Baseline distortions



(b) %Δ when p_x decreases

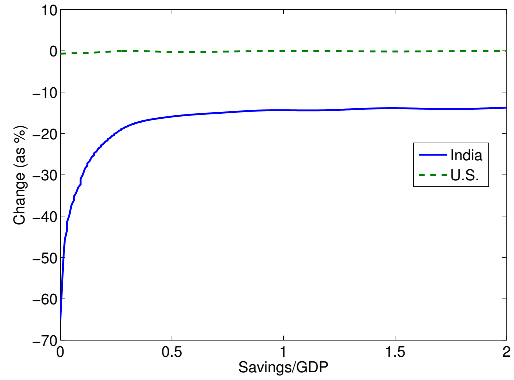
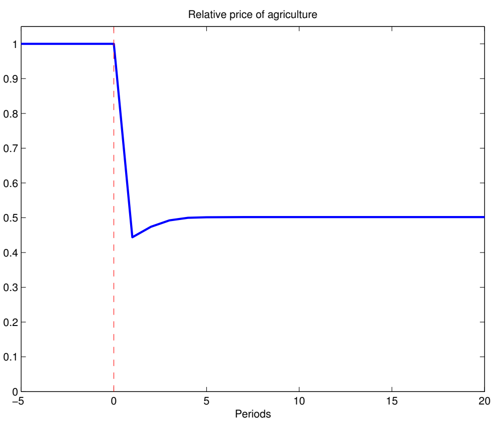
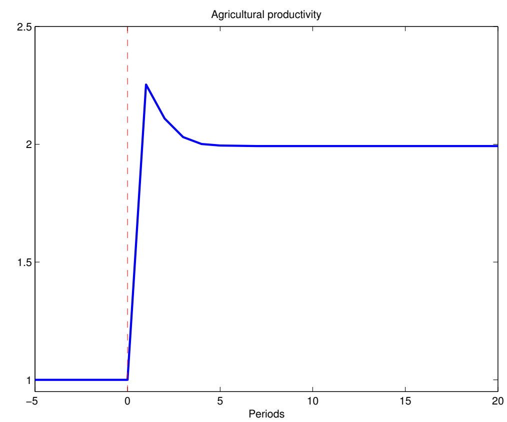


Figure 7: Dynamics of a surprise decrease in p_x in Indian economy at $t = 0$. Initial steady state values are normalized to one.

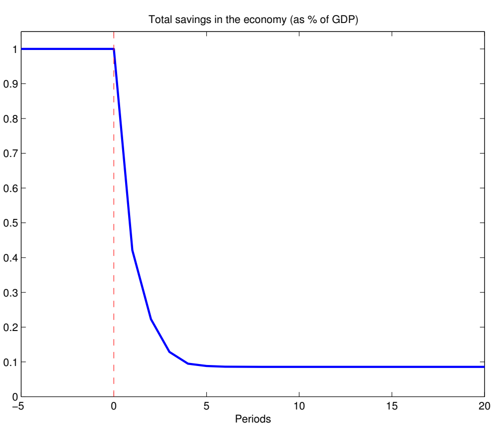
(a) Relative price of agriculture



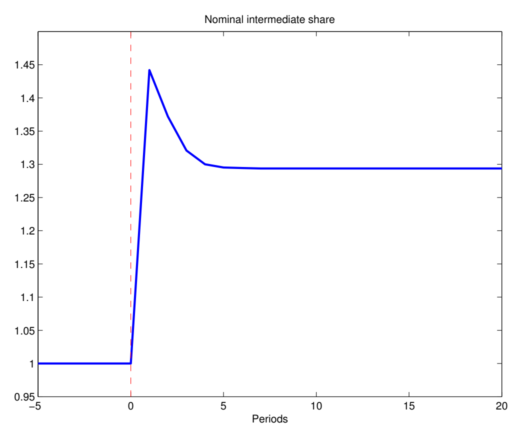
(b) Agricultural productivity



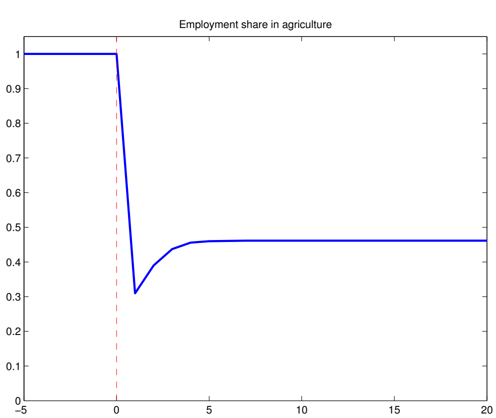
(c) Total Savings/GDP



(d) Nominal intermediate share



(e) Employment share in agriculture



Appendices (for online publication)

A Uninsured Shocks as a Reduced-Form Distortionary Tax Wedge

In this section, I show that the model developed in the paper is isomorphic to a generic tax wedge. Moreover, this wedge can be decomposed to isolate the impact of risk.

Define the "*ex post* economy" as the economy in which all decisions are made after the realization of shock z. The household problem in the *ex post* economy is

$$\begin{aligned} & v(z,b) = \max_{x,n_a,b'} \quad \alpha \log(c_a - \bar{a}) + (1-\alpha)\log(c_m) + \beta \int_Z v(z',b')dQ(z) \\ s.t. \quad & p_a c_a + c_m + p_a b' = zAx^{\psi} n_a^{\eta} - (1+\phi(z,b))x + w(1-n_a) + p_a(1-\delta)b + \Phi(z,b) \\ & b \geq 0. \end{aligned}$$

The link between the two models is the tax $\phi(z,b)$ on intermediates, which is rebated back to households as $\Phi(z,b)$. The rest of the model is identical to that in the main body of the paper. Proposition 3 shows that the tax $\phi(z,b)$ can be designed to implement the equilibrium of the incomplete markets model developed in this paper, and moreover, is log separable in z and b, so that the risk-driven distortion can be isolated.

Proposition 3. *For an economy with TFP A, there exists a tax function $\phi(z,b)$ such that the equilibrium of the ex post economy is identical to the incomplete markets economy. The tax can be decomposed as* $1+\phi(z,b) =$

$\phi^{time}(z) \times \phi^{risk}(b)$ *where*

$$\phi^{time}(z) = \frac{z^{1/(1-\eta)}}{\int_Z z^{1/(1-\eta)} dQ(z)}$$

$$\phi^{risk}(b) = \frac{\int_Z z^{1/(1-\eta)} dQ(z)}{\int_Z z^{1/(1-\eta)} \left(\frac{\widetilde{u}'(y(x^I(b),z))}{\mathbb{E}_z(\widetilde{u}'(y(x^I(b),z))} \right) dQ(z)}$$

and $x^I(b)$ *is the decision rule the intermediate choice for the baseline incomplete markets model.*

Proof. Assume an equilibrium of the baseline model economy (i.e. the model in the main body of the paper) characterized by decision rules $x^I(b)$, $b'^I(b,z)$, invariant distribution $\mu(b)$, and equilibrium price p_a.

Assume that the equilibrium price in the *ex post* economy is equal to p_a. First, this is sufficient to guarantee that the choice of x is the same for all (z,b). The first order condition for x in the *ex post* economy for an individual with savings b and shock realization z, after solving for $n_a(z,b)$, is

$$Ap_A^{1/(1-\eta)} F'(x) z^{1/(1-\eta)} = p_x(1 + \phi(z,b))$$

When

$$1 + \phi(z,b) = \frac{z^{1/(1-\eta)}}{\int_Z z^{1/(1-\eta)} \left(\frac{\widetilde{u}'(y(x^I(b),z))}{\mathbb{E}_z(\widetilde{u}'(y(x^I(b),z))} \right) dQ(z)},$$

it follows that $x^{IM}(b)$ is the only solution to this problem, and is independent of the realization of z. From there, the fact that the transfer is rebated back to the household insures that profit is the same for all individuals with individual state (z,b) in both the *ex post* economy and the baseline economy. The transfer of tax revenue back to households guarantees that income is identical across economies as well. Since income is the same, savings decisions are the same as well, thus implying that the invariant distribution across savings is identical.

Production and income decisions are therefore identical in the two economies. Since markets clear in the incomplete markets economy, they must also in the *ex post* economy. Since p_a is the unique equilibrium price, this implies that the equilibrium in the *ex post* economy is identical to that of the baseline model economy. ■

The portion of the tax $\phi^{time}(b)$ simply accounts for the change in timing between the models, and is irrelevant for the risk-driven misallocation. $\phi^{risk}(b)$ is the share of the distortion generated by increased relative risk aversion among poor households. It implies a positive tax on all households ($\phi^{risk} > 1$), but a higher tax for poor households. Therefore, uninsured shocks work by misallocating resources away from low wealth households in the same way as models of explicit input market distortions, though the distortion instead comes from the inability of households to insure consumption.

B Additional Results

B.1 Impact of τ and δ across countries

In this section, I provide the counterpart of results presented in Section 7 p_x.

Table 11: Agricultural productivity as τ changes

	$A = 0.22$	$A = 1$
$\tau = 0.57$	0.023	0.663
$\tau = 0$	0.039	1.000
% increase	72.26	50.83

Table 12: Agricultural productivity as δ changes

	$A = 0.22$	$A = 1$
$\delta = 0.15$	0.023	1.000
$\delta = 0.03$	0.026	1.000
% increase	14.4	0.00

B.2 Additional Results on GE Effects

Why does the model predict smaller cross-country variation in the real intermediate share than the nominal intermediate share? I show here that the general equilibrium variation in p_a necessarily dampens the effect on the real intermediate share, while amplifying differences in the nominal share.

To do so, I study different variations of the Indian model economy. I begin from the complete markets equilibrium. I then eliminate the Arrow securities but still hold the price constant at its complete markets equilibrium level. That is, households face risk, but the relative agricultural price is not allowed to adjust in response. These results are in row two of Table 8. Both the real and the nominal intermediate share are 23 percent lower than in the complete markets economy, which isolates the direct impact of risk on intermediate choices. This lower intermediate intensity then lowers the marginal return to labor, and therefore decreases agricultural employment to 59 percent of its complete markets equilibrium level. The drop in employment makes up for nearly all of the decrease in intermediate intensity, as agricultural productivity is nearly identical to its complete markets benchmark.

I then allow the relative price p_a to adjust to its incomplete markets equilibrium level. This is 29 percent higher than the complete markets counterpart (row three of Table 8). As p_a increases, the real intermediate share actually increases by 9 percent as the marginal return to intermediates increases, but still remains 16 percent below its complete markets level. The increase in the real share is smaller than the increase in the price (because the price of subsistence $p_a\bar{a}$ is also increasing), so the nominal share drops ever lower to 66 percent of its complete markets level. The price increase causes the nominal share to decrease by 17 percent, or 37 percent relative to its complete markets level. Moreover, the price increase induces a flow of employment into agriculture. The price increase alone increases the agriculture employment share by

147 percent (from 0.59 to 1.46), or 46 percent relative to its complete markets level.

Taken together, risk has two effects on agricultural productivity. First, it lowers the real intermediate share. This effect is somewhat dampened by the general equilibrium increase in the price p_a. This same effect, however, generates a large increase in agricultural employment, which amplifies the drop in agricultural productivity relative to a complete markets model.

Table 13: GE Effects

	X/Y	$p_x X/p_a Y_a$	N_a	Y_a/N_a	p_a
CM, p_a^{CM}	1.00	1.00	1.00	1.00	1.00
IM, p_a^{CM}	0.79	0.79	0.59	1.00	1.00
IM, p_a^{IM}	0.86	0.66	1.46	0.76	1.29

Table notes: Results are for the Indian model economy. p_a^{CM} is the equilibrium price for the complete markets economy, while p_a^{IM} is the equilibrium price for the incomplete markets market economy. The first row is normalized to one.

B.3 Changes in the Variance of z

I also investigate the importance of the shock distribution by varying the standard deviation of the underlying normal distribution σ_z, while holding the support $\underline{z}$ and $\overline{z}$ fixed. The results are presented in Table 14.

Table 14: Model Results for Different σ_z

	Labor Productivity Gap		$p_x X/p_a Y_a$		N_a *(%)*	
Economy	Agriculture	Aggregate	Rich	Poor	Rich	Poor
Model with						
$\sigma_z = 0.50$	45.3	7.8	0.40	0.25	1.2	50.0
$\sigma_z = 0.75$	43.2	6.4	0.39	0.25	1.0	34.9
$\sigma_z = 1.00$	41.7	5.7	0.39	0.25	0.7	24.0

Higher standard deviations result in smaller productivity differences. However, all of the difference comes from the amount of labor in agriculture. Intuitively, the result is due to the interaction of the low utility weight on agricultural consumption, α, and subsistence requirements $\bar{a}$. Because α is so low, total agricultural output needs to be roughly $\bar{a}$. When σ_z is low, the price p_a must increase to incentivize people to produce with risky intermediate inputs. As σ_z increases, a larger and larger number of households "luck" into a good shock, and are able to produce $\bar{a}$ and the equilibrium price remains low. This impact is counteracted in part by the fact that households are subject to more risk. Hence, a doubling in the standard deviation of shocks implies only an 8 percent decrease in the agricultural productivity gap.

B.4 Different Shocks or Different Responses?

An alternative explanation to the one highlighted in this paper is that poor countries could simply face different exogenous agricultural shocks. I explore this alternative hypothesis using detailed information on historical rainfall fluctuations. Aggregating rainfall data to study cross-country variation present some difficulties however. For one, agriculture is not uniformly produced across a country's geographic regions. If production occurs in areas that have more stable rainfall, for example, a country-wide average of rainfall variation will overstate the risk faced by farmers. I correct for these issues using the Global Agro-Ecological Zones (GAEZ) data produced by the FAO and International Institute for Applied Systems Analysis. The GAEZ data is spatial grid data on historical rainfall at the 5 arc minute resolution, similar to the TRMM data used in previous sections, and includes approximately 9 million cells.[18] The advantage of the GAEZ is that for the year 2000, it contains the internationally priced value of harvest in each cell. I use this to compute harvest-weighted

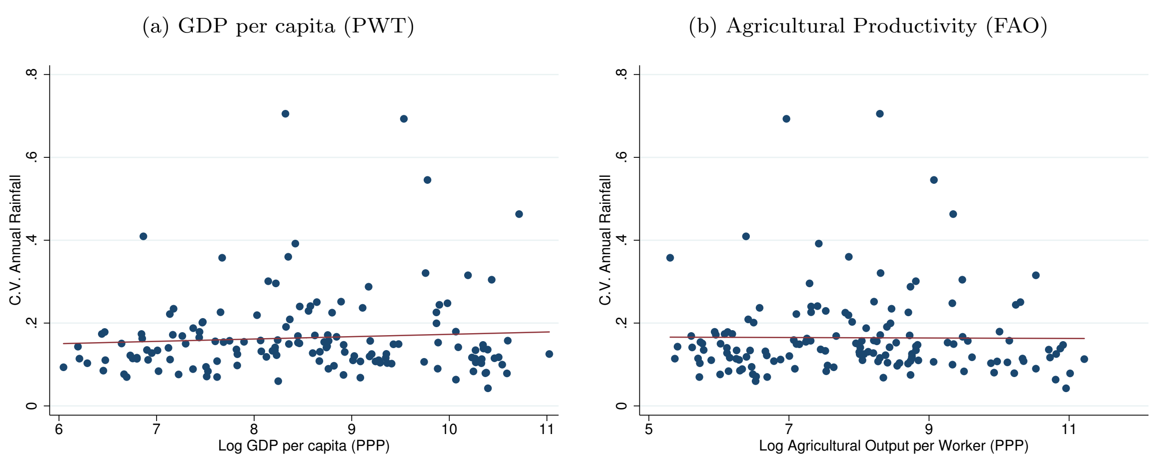
[18] The GAEZ includes a number of other measures of agricultural suitability. See recent work by Adamopoulos and Restuccia (2015) for use of these alternative measures of agricultural suitability in a cross-country context.

country-level rainfall for the years 1980-2000, and then compute the country-level variation in rainfall over that period. More specifically, I use arcGIS to assign each cell i to its respective country j, denoting the set of cells in country j as $\mathcal{C}_j$. Then, for each country j, I compute the harvest-weighted annual rainfall as

$$rain_{jt} = \sum_{i \in \mathcal{C}_j} rain_{ijt} \times \left(\frac{Y_{ij}}{\sum_{k \in \mathcal{C}_j} Y_{kj}} \right)$$

where $rain_{ijt}$ is annual rainfall in cell i in country j in year $t \in \{1980, \ldots, 2000\}$ and Y_{ij} is the internationally priced value of annual harvest in 2000. Figure 8 shows the relationship between the coefficient of variation of the country-level rainfall estimates and both GDP per capita and agricultural output per worker for 147 countries in the year 2000.

Figure 8: Rainfall Variation Across Countries



I find no evidence of a trend in either relationship, and Table 15 confirms this with a simple linear regression of the coefficient of variation of annual rainfall (measured as the z-score) on the two productivity measures. A one standard deviation increase in the rainfall c.v. is associated with a one percent decrease in agricultural productivity, not nearly large enough to matter for agricultural productivity differences across countries. The result echoes recent work by Adamopoulos and Restuccia (2015) who show that natural disadvantages (soil and land quality, for example) are not responsible for low agricultural productivity in poor countries. Instead, these results suggests that the differential response to risk across countries is key for understanding the relationship between risk and intermediate inputs, not variation in the exogenous shocks themselves.

Table 15: Relationship between productivity and rainfall variability

	Log GDP per capita	Log agricultural output per worker
Constant	8.529***	7.956***
	(0.104)	(0.128)
normalized c.v. rainfall	0.090	−0.013
	(0.105)	(0.127)
R^2	0.005	0.000

Table notes: Standard errors are in parentheses. Significance at 0.01, 0.05, 0.1 levels denoted by ***, **, and *. The independent variable is z-score of the coefficient of variation for harvest-weighted annual rainfall 1980-2000.

B.5 Correlation Between Crops and Consumption Volatility

I correlate the measure of consumption volatility used to calibrate the model with crops harvested. In particular, I first compute the average harvest value share of castor, cotton, maize, paddy, pigeon pea, sorghum, and wheat for each household in the ICRISAT panel. I then correlate them with the coefficient of variation and standard deviation of the growth rate of consumption, where consumption is in equation (5.2) in the main text. There is no correlation between crop choice and the two measures of consumption volatility.

Table 16: Partial correlation of harvest share with consumption volatility measures

	σ consumption growth	*cv* consumption
castor	0.005	0.013
cotton	0.030	0.069
maize	-0.007	0.002
paddy	-0.087	-0.065
pigeon pea	-0.049	-0.055
sorghum	0.020	-0.027
wheat	-0.042	-0.078

Table notes: Significance at 0.01, 0.05, 0.1 levels denoted by ***, **, and *.

B.6 Changes in Productivity As Shocks Become Insurable

In the paper, I compare the complete and incomplete markets regimes. Here, I allow for some fraction of the shocks to be insurable. In particular, I re-write the production function as

$$y_a = e^{z_1+z_2} A x^{\psi} n_a^{\eta}$$

where z_1 and z_2 are both normal random variables with mean zero and $\sigma_1+\sigma_2 = 0.48$. That is, together, the shocks have the same mean and variance as the shock process in the paper. Here, however, I assume that z_1 is uninsurable while z_2 is insurable. As $\sigma_2 \to 0.48$, the results converge to the complete markets case, while $\sigma_2 \to 0$ implies the baseline results.

Even when a large proportion of shocks are insurable, there is still a substantial gap from the results in which all shocks are insurable. This highlights the importance of downside risk. While increasing the proportion of variance insured decreases the likelihood of receiving a low uninsured shock, it does not change the fact that households put more weight on those realizations, which somewhat limits the impact of decreasing uninsurable risk.

Table 17: Changing % of insurable variance

	Labor Productivity Gap		p_xX/p_aY_a		N_a *(%)*	
Economy	Agriculture	Aggregate	Rich	Poor	Rich	Poor
% of variance insurable						
0	45.0	7.8	0.40	0.26	1.2	0.50
20	41.4	7.3	0.40	0.28	1.2	0.45
60	39.0	7.1	0.40	0.31	1.2	0.43
80	38.8	6.9	0.40	0.32	1.2	0.42
100	34.5	6.4	0.40	0.40	1.2	0.34

C Data Sources and Construction

C.1 Productivity and Intermediate Input Share Statistics

I make use of Prasada Rao (1993), which is the data underlying Restuccia et al. (2008).

Intermediate Shares As in the text, the domestic intermediate share in agriculture of country j is

$$\widehat{X}^j := \frac{p_x^j X^j}{p_a^j Y_a^j} \tag{C.1}$$

This measure is not directly reported in Prasada Rao (1993). He does however, report the real intermediate share in agriculture, defined as

$$\widehat{X}^{j*} := \frac{p_x^* X^j}{p_a^* Y_a^j} \tag{C.2}$$

where p_x^* and p_a^* are international prices of intermediate inputs and agricultural output. Combining equations (C.1) and (C.2), it is possible to write the domestic intermediate share as

$$\widehat{X}^j = \widehat{X}^{j*}\left(\frac{p_x^j/p_x^*}{p_a^j/p_a^*}\right) \tag{C.3}$$

The price ratio in equation (C.3) can be calculated from reported purchasing power parities

$$\begin{aligned} PPP_a^j &= \frac{p_a^j}{p_a^*} \\ PPP_x^j &= \frac{p_x^j}{p_x^*} \end{aligned}$$

where p_a^* and p_x^* are international (unreported) prices and (p_a^j, p_x^j) are (unreported) domestic prices for country j. The purchasing power parities are normalized to one in a baseline country, which in Prasada Rao (1993) is the USA. Therefore, $PPP_a^{US} = PPP_x^{US} = 1$, implying $\widehat{X}^{US} = \widehat{X}^{US*}$. Therefore, calculating the domestically priced intermediate share of all other countries reduces to

$$\widehat{X}^j = \widehat{X}^{j*}\left(\frac{PPP_x^j}{PPP_a^j}\right) \tag{C.4}$$

As mentioned, the real intermediate share and the ratio of PPPs are both reported, so this is sufficient to define the domestically priced intermediate input share. The poor group group of countries has, on average, a domestically priced intermediate input share of 0.09 and a real intermediate input share of 0.13. The right hand side of equation (C.4) is the statistic reported in Figure 1b. The horizontal axis, GDP per capita, is real GDP per capita for 1985, variable cgdp from the Penn World Tables version 7.0 (PWT).

C.2 Three Sector Comparison: UN System of National Accounts

For the comparison of agriculture to manufacturing and services, I use the publicly available U.N. System of National Accounts. For each sector, I use "Output, at basic prices" as output and "Intermediate consumption, at purchaser's prices" as intermediate inputs. The sectors are defined by aggregating the following industry codes:

1. Agriculture: A, B
2. Manufacturing: C, D, E, F
3. Services: G, H, I, L, M, N, O, P
4. Non-agriculture: Entire Economy - A - B

I use all countries that have a complete set of required data, which is maximized in 2005 (though the results are robust to any other choice of years). The final dataset includes 87 countries. Note that the intermediate share in agriculture derived from the UN statistics and the FAO statistics may differ. This is due to the fact that the UN statistics includes intermediate inputs produced in the agricultural sector, while the FAO statistics only consider nonagricultural intermediate inputs.

C.3 Micro Evidence: LSMS and NASA Weather Data

Weather The weather data is downloaded from the Goddard Earth Sciences Data and Information Center, online here http://goo.gl/nlFomb. The data includes 0.25×0.25 degree monthly rainfall estimates on latitudes [-50, 50] and longitudes [-180,180] every month form January 1998 - current (April 2015) for 576,000 monthly data points around the world.

LSMS The LSMS data is available from the World Bank. See http://iresearch.worldbank.org/lsms/lsmssurveyFinder.htm for a convenient survey locator. Since the goal is to construct variation in weather dating back to only 1998, I restrict attention to surveys completed after 2005. The datasets used must meet four criteria:

1. Have GPS coordinates for households to merge with weather data

2. Fertilizer quantities and either prices or total value to compute prices.
3. One year previous livestock holdings

Malawi, Niger, Tanzania, and Uganda satisfy the three criteria.

D Proofs

D.1 An Additional Lemma for the Proof of Proposition 1

To prove the result, I first characterize the the equilibrium of an I economy with TFP A^2 and $\bar{a} = 0$ in terms of an economy with TFP A^1 and $\bar{a} = 0$. This is done in Lemma 1 below.

Lemma 1. *Consider two I economies characterized by TFP levels A^1 and A^2, both with $\bar{a} = 0$. Denote the equilibrium for economy 1 as $(x^1, n_a^1(z), p_a^1)$. Then the equilibrium for economy 2, $(x^2, n_a^2(z), p_a^2)$ can be characterized as*

$$
\begin{aligned}
n_a^2(z) &= n_a^1(z) \\
x^2 &= \left(\frac{A^2}{A^1}\right) x^1 \\
p_a^2 &= \left(\frac{A^1}{A^2}\right)^{\psi} p_a^1
\end{aligned}
$$

Proof. Two things must be checked for the proposed allocation to be a competitive equilibrium. First, the proposed equilibrium must satisfy the household optimization problem. That is, if $(p_a^1, x^1, n_a^1(z))$ is an equilibrium in economy 1, then $(p_a^2, x^2, n_a^2(z))$ satisfies the farmer's optimization problem in economy 2. Second, markets must clear. These are considered in turn.

Optimization Problem The first thing to check is that the labor choice is identical between the two. Using the decision rules, I can check this using the first order conditions for $n_a^1(z)$ and $n_a^2(z)$.

$$\frac{n_a^1(z)}{n_a^2(z)} = \left(\frac{p_a^1 A^1 (x^1)^\psi}{p_a^2 A^2 (x^2)^\psi}\right)^{1/(1-\eta)}$$

Plugging in (p_a^2, x^2) implies

$$\frac{n_a^1(z)}{n_a^2(z)} = 1$$

For simplicity, I drop the superscript on $n_a(z)$, with the understanding that they are identical in both economies.

Next up is to check if x^2 satisfy the required first order conditions, given that x^1 satisfies the first order condition in Economy One. Note that when $\bar{a} = 0$, the production utility for a given income y can be written as

$$\begin{aligned} v^p(y) &= \alpha \log(c_a^1) + (1-\alpha)\log(c_m^1) \\ &= \Omega - \alpha \log(p_a^1) + \log(y) \end{aligned} \tag{D.1}$$

where $\Omega = \alpha \log(\alpha) + (1-\alpha)\log(1-\alpha)$. Denote the income of a farmer who chooses intermediates x and gets hit with shock z in economy $j = 1, 2$ as

$$y^j(x, z) = p_a^j A^j z x^\psi n_a(z)^\eta - x + (1 - n_a(z))A^j$$

Plugging in the proposed equilibrium yields the following relationship

$$y^2(x^2, z) = \left(\frac{A^2}{A^1}\right) y^1(x^1, z) \tag{D.2}$$

Equation (D.1) implies that

$$x^j = \arg\max_x \int_Z \log(y^j(x, z)) dQ(z)$$

After plugging in the optimal values for $n_a(z)$, the first order condition for this problem can be written as

$$\int_{\underline{z}}^{\bar{z}} \left(\frac{\psi p_a^j z A^j x^{j\psi-1} n_a(z)^\eta - 1}{y^j(x, z)}\right) = 0$$

Plugging in the proposed equilibrium yields a relationship between economies one and two

$$\int_{\underline{z}}^{\bar{z}} \left(\frac{\psi p_a^2 z A^2 x^{2\psi-1} n_a(z)^\eta - 1}{y^2(x,z)} \right) = \left(\frac{A^1}{A^2} \right) \int_{\underline{z}}^{\bar{z}} \left(\frac{\psi p_a^1 z A^1 x^{1\psi-1} n_a(z)^\eta - 1}{y^1(x^j,z)} \right)$$

Since an equilibrium is assumed in economy one, it follows then that

$$\int_{\underline{z}}^{\bar{z}} \left(\frac{\psi p_a^2 z A^2 x^{2\psi} n_a(z)^\eta - 1}{y^2(x,z)} \right) = 0$$

Therefore, the proposed economy two equilibrium satisfies a household's optimization problem.

Market Clearing Aggregate sector a output for economy $j = 1, 2$ is

$$Y_a^j = A x^{j\psi} \mathbb{E}_z(z n_a(z)^\eta)$$

Thus,

$$\frac{Y_a^1}{Y_a^2} = \left(\frac{A^1}{A^2} \right) \left(\frac{x^1}{x^2} \right)^\psi \tag{D.3}$$

Therefore, at the proposed equilibrium,

$$\frac{Y_a^1}{Y_a^2} = \left(\frac{A^1}{A^2} \right)^{1+\psi} \tag{D.4}$$

For any $\bar{a} \geq 0$, the total demand for sector a consumption is given by

$$D_a^j = (1-\alpha)\bar{a} + \frac{\alpha}{p_a^j} \mathbb{E}_z[y^j(X^j, z)] \tag{D.5}$$

Using equation (D.2),

$$\frac{\mathbb{E}_z[y^1(x^1,z)]}{\mathbb{E}_z[y^2(x^2,z)]} = \frac{A^1}{A^2} \tag{D.6}$$

Since $\bar{a} = 0$, equations (D.5) and (D.6) and the prices p_a^1 and p_a^2 imply that

$$\frac{D_a^1}{D_a^2} = \left(\frac{A^1}{A^2} \right)^{1+\psi} \tag{D.7}$$

Since the proof assumes an equilibrium in economy 1, equations (D.4) and (D.7) imply $Y_a^2 = D_a^2$ so that the agricultural output market clears in economy two. Since the labor market in sector m clears trivially, Walras' Law implies that the sector m output market also clears. ■

D.2 Proof of Proposition 1

Proof. With Lemma 1 in hand, the three claims of the proposition follow quickly.

D.2.1 $n_a(z)$ is independent of A

This follows directly from Lemma 1.

D.2.2 The intermediate input share is independent of A

Denote $\hat{X}^j$ as the intermediate good share in economy $j = 1, 2$, so that $\hat{X}^j$ is defined as

$$\hat{X}^j = \frac{x^j}{p_a^j Y_a^j} \tag{D.8}$$

First, note that total agricultural output in economy j is given as

$$Y_a^j = A^j (x^j)^{\psi} \mathbb{E}_z (z n_a^j(z)^{\eta}) \tag{D.9}$$

Using the fact that $n_a^1(z) = n_a^2(z)$ and plugging (D.9) into (D.8) gives

$$\frac{\hat{X}^1}{\hat{X}^2} = \left(\frac{x^1}{x^2}\right)^{1-\psi} \left(\frac{p_a^2}{p_a^1}\right) \left(\frac{A^2}{A^1}\right)$$

Plugging in the equilibrium found in Lemma 1, this gives

$$\begin{aligned} \frac{\hat{X}^1}{\hat{X}^2} &= \left(\frac{A^1}{A^2}\right)^{1-\psi} \left(\frac{A^1}{A^2}\right)^{\psi} \left(\frac{A^2}{A^1}\right) \\ &= 1 \end{aligned}$$

Since A^1 and A^2 are arbitrary, this completes the proof.

D.2.3 No increase in productivity relative to C economy

For any two economies characterized by TFP A^1 and A^2 and complete markets (the C economy), it is easy to show that in equilibrium,

$$\begin{aligned} n_a^1 &= n_a^2 \\ x^2 &= \left(\frac{A^2}{A^1}\right) x^1 \end{aligned}$$

Since this is the same as in the incomplete markets model (the I economy), relative agricultural labor productivity between the two economies is equal in both.

■

D.3 Proof of Proposition 2

Proof. Consider the equilibrium for economy 1 with TFP equal to A^1. Denote this equilibrium $(p_a^1, x^1, n_a^1(z))$. Suppose that the intermediate good share is $\hat{X}^1 < \psi$. Define x^{1C} to be the optimal choice of the farmer who faces p_a^1 but with complete markets. We know that the intermediate good share is $\hat{X}^{1C} = \psi$. Therefore, the ratio is

$$\frac{\hat{X}^1}{\hat{X}^{1C}} = \frac{\hat{X}^1}{\psi} = \left(\frac{x^1}{x^{1C}}\right)^{(1-\eta-\psi)/(1-\eta)}$$

Thus, we can write $\hat{X}^1$ as

$$\hat{X}^1 = \psi \left(\frac{x^1}{x^{1C}}\right)^{(1-\eta-\psi)/(1-\eta)}$$

Similarly, it follows that in Economy 2,

$$\hat{X}^2 = \psi \left(\frac{x^2}{x^{2C}}\right)^{(1-\eta-\psi)/(1-\eta)}$$

These equations show that the intermediate good share is directly related to how "far" the optimal choice of x is from the choice x^C. What's left to show is that when $\bar{a} > 0$ and $A^1 > A^2$,

$$\frac{x^1}{x^{1C}} > \frac{x^2}{x^{2C}}$$

This follows from the fact that, when $\bar{a} > 0$, relative income net of subsistence,

$$\frac{y^1(z) - p_a^1 \bar{a}}{y^2(z) - p_a^2 \bar{a}}$$

is decreasing in z. ■