By reducing the negative correlation between local prices and productivity shocks, trade liberalization changes the volatility of returns. In this paper, we explore the second moment effects of trade. Using forty years of agricultural micro-data from India, we show that trade increased farmer’s revenue volatility, causing farmers to shift production toward crops with higher mean and lower variance yields. We then incorporate producers’ optimal allocation of resources across risky production technologies into a many location, finite good quantitative general equilibrium Ricardian trade model with flexible bilateral trade costs. The model yields closed form solutions for the equilibrium specialization of farmers across crops and generates two somewhat surprising results: (1) when farmers are risk averse, trade can make farmers worse off; and (2) when trade is costly, insurance can make farmers worse off. Finally, we structurally estimate the model—recovering farmers’ unobserved risk-return preferences from the gradient of the mean-variance frontier at their observed crop choice—to quantify the second moment welfare effects of trade. We find that while greater trade openness increased farmer’s volatility, the welfare cost of this increased volatility was dwarfed by the first moment gains from trade.

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1 Introduction

While trade liberalization increases average returns through specialization, it also affects the volatility of returns by reducing the negative correlation between local prices and productivity shocks. When production is risky, producers are risk averse, and insurance markets are incomplete—as is the case for farmers in developing countries—the interaction between trade and volatility may have important welfare implications. Yet we still have a limited understanding of the relationship between trade and volatility. In particular, does volatility magnify or attenuate the traditional first moment gains from trade, and what (if any) complementary policies ought to be undertaken to maximize the gains from trade?

In this paper, we empirically, analytically, and quantitatively explore the second moment effects of trade. Using forty years of agricultural micro-data from India, we show empirically that trade increased farmer’s revenue volatility, causing farmers to shift production toward crops with higher mean and lower variance yields. We then incorporate producers’ optimal allocation of resources across risky production technologies into a many country, many good, quantitative general equilibrium Ricardian trade model. The model yields analytical expressions for the equilibrium allocation of resources and generates straightforward relationships between observed equilibrium outcomes and underlying structural parameters, allowing us to quantify empirically the second moment welfare effects of trade. We find that the welfare costs of the increased volatility due to greater trade openness were dwarfed by the first moment gains. Counterfactuals suggest that better insurance markets would have had limited impacts on the size of these gains as the direct benefits from being able to insure the increased risk would be offset by general equilibrium price effects as farmers move away from local consumption goods toward the production of risky cash crops for export.

Rural India—home to roughly one-third of the world’s poor—is an environment where producers face substantial risk. Even today, less than half of agricultural land is irrigated, with yields driven by the timing and intensity of the monsoon and other more localized rainfall variation. Access to agricultural insurance is very limited, forcing farmers to face the brunt of the volatility, see e.g. Mahul, Verma, and Clarke (2012). Furthermore, many are concerned that the substantial fall in trade costs over the past forty years (due to expansions of the Indian highway network and reductions in tariffs) has amplified the risk faced by farmers. For example, the New York Times, in an article entitled “After Farmers Commit Suicide, Debts Fall on Families in India”, writes:

“When market reforms were introduced in 1991, the state scaled down sub-
sidies and import barriers fell, thrusting small farmers into an unforgiving global market. Farmers took on new risks, switching to commercial crops and expensive, genetically modified seeds... They found themselves locked in a whiteknuckle gamble, juggling everlarger loans at exorbitant interest rates, always hoping a bumper harvest would allow them to clear their debts, so they could take out new ones. This pattern has left a trail of human wreckage.” (2/22/2014).

Using a dataset containing the annual price, yield, and area planted for each of 15 major crops across 311 districts over 40 years matched to imputed bilateral travel times along the evolving national highway network, we confirm that reductions in trade costs did affect volatility. In particular, we show that: (1) reductions in trade costs due to the expansion of the highway network reduced in magnitude the negative correlation between prices and yields, thereby increasing farmers’ revenue volatility; (2) the reductions in trade costs caused farmers to reallocate their land toward crops with higher and less volatile yields; and (3) the reallocation toward crops with less volatile yields is less pronounced in districts where farmers have better access to banks.

We next develop a quantitative general equilibrium model of trade and volatility. To do so, we first construct a many country Ricardian trade model with a finite number of homogenous goods and arbitrary (symmetric) bilateral trade costs. We circumvent the familiar difficulties arising from corner solutions as follows: rather than assuming that each bilateral pair is separated by a single iceberg trade cost, we assume that there are many (infinitesimal) traders who randomly match to farmers, each of whom has a distinct iceberg trade cost drawn from a Pareto distribution. We show that this assumption allows equilibrium prices to be written as a log-linear function of yields in all locations, with the constant elasticities determined by the matrix of shape parameters governing the distribution of bilateral trade costs. Furthermore, in the absence of volatility, we derive an analytical expression for the equilibrium pattern of specialization across countries that depends solely on exogenous model fundamentals (i.e. the distribution of trade costs and productivities). To our knowledge, this is the first closed form expression for the pattern of specialization in a many-country many-good Ricardian model.1

To incorporate volatility in the model, as in Newbery and Stiglitz (1984), we assume that producers allocate their factor of production prior to the realization of productivity shocks, a particularly reasonable assumption in the agricultural context. By applying

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1In their seminal paper, Eaton and Kortum (2002) derive an analytical expression for the patterns of trade in a many-country Ricardian trade model with a continuum of goods (rather than a finite number of goods, as here). However, their expression depends on the vector of equilibrium wages, which cannot (generically) be derived in closed form.
tools from the portfolio allocation literature (see e.g. Campbell and Viceira (2002)), we are able to retain tractable expressions for the equilibrium pattern of specialization given any set of average crop productivities and any variance-covariance matrix governing the volatility of productivities across crops. In particular, we show that the entire model remains sufficiently tractable to yield both qualitative predictions that are consistent with the stylized facts mentioned above and structural estimating equations that allow us to quantify the role of volatility in trade.

This framework reveals several somewhat surprising implications from incorporating second moment effects of trade. First, when farmers are risk averse, opening up to trade can make farmers worse off. Intuitively, this occurs when farmers allocate most of their time toward the production of goods in which they do not have a comparative advantage (as defined by the relative productivity ratios) in order to reduce their exposure to risk. If opening up to trade increases the relative price of the comparative advantage good, the real returns of the farmers will fall, reducing their welfare. In other cases, however, the gains from trade can be larger than in standard models if farmers are risk averse and production is risky as trade provides farmers a technology to reduce risk: by de-coupling consumption from production, farmers can reduce risk by reallocating their time toward a less risky bundle. The second implication is that, when trade is costly, improving farmers’ access to insurance can make them worse off. Intuitively, better insured farmers may allocate production more toward risky “cash crops”, which worsens the terms of trade by reducing the price the farmers receive for the cash crops and increasing the price the farmers must pay for their consumption bundle.

Finally, we take advantage of the tractability of the model to estimate the model and empirically quantify the second moment welfare effects of trade. The model implies that the unobserved trade costs determine the elasticity of local prices to yield shocks in all locations and that farmers’ unobserved risk-return preferences shape the gradient of the mean-variance frontier at the farmer’s observed crop choice. Conveniently, we show that these two relationships can be reduced to two linear equations and so both unobserved trade costs and risk-return preferences can be recovered via ordinary least squares. Reassuringly, we find that expansion of the highway network not only decreased the responsiveness of local prices to local yields (as already shown in Stylized Fact 1B) but also increased the responsiveness of local prices to yields elsewhere, with the bilateral trade costs between $i$ and $j$ recoverable from the elasticity of $i$’s price to $j$’s yield shocks. As a further check on the parameter estimates, the estimates of risk-return tradeoffs inferred from observed choices along the mean-variance frontier are strongly correlated with spatial and temporal variation in access to rural banks. We use these parameter estimates to
decompose the gains from trade and show that the costs of volatility (the second moment losses) are about one fifth the size of the first moment gains from trade. Furthermore, while the gains from trade would have been larger had farmers had access to perfect insurance, the increase is limited since farmers would allocate resources toward the production of risky “cash crops” for export, driving down the prices of these crops (and average real returns) and driving up the cost of the consumption bundle.

This paper relates to a number of strands of literature in both international trade and economic development. The theoretical literature on trade and volatility goes back many years (see Helpman and Razin (1978) and references cited therein). In a seminal paper, Newbery and Stiglitz (1984) develop a stylized model showing that trade may actually be welfare decreasing in the absence of insurance (although to obtain this result, in contrast to our model they require that farmers and consumers differ in their preferences and do not consume what they produce). Eaton and Grossman (1985) and Dixit (1987, 1989a,b) extend the theoretical analysis of Newbery and Stiglitz (1984) to incorporate imperfect insurance and incomplete markets. Our paper incorporates the intuition developed in these seminal works into a quantitative trade model that is sufficiently flexible (e.g. by incorporating many goods with arbitrary variances and covariances of returns and flexible bilateral trade costs) to be taken to the data. More recently, several papers have explored the links between macro-economic volatility and trade, see e.g. Easterly, Islam, and Stiglitz (2001); di Giovanni and Levchenko (2009); Karabay and McLaren (2010); Lee (2013). Our paper, in contrast, focuses on the link between micro-economic volatility and trade, which has a number of advantages, including allowing us to observe the underlying local (weather) shocks and changes to trade costs.

Most closely related to our paper are the works of Burgess and Donaldson (2010, 2012) and Caselli, Koren, Lisicky, and Tenreyro (2014). Burgess and Donaldson (2010, 2012) use an Eaton and Kortum (2002) framework to motivate the empirical strategy that studies the relationship between famines and railroads in colonial India. Caselli, Koren, Lisicky, and Tenreyro (2014) also use an Eaton and Kortum (2002) framework to quantify the relative importance of sectoral and cross-country specialization in a world of globally sourced intermediate goods. We see our paper as having three distinct contributions relative to these papers: first, we depart from the Eaton and Kortum (2002) framework and develop

\[2\] Despite focusing on intra-national trade in the same country, India, there are also important differences between modern India and the colonial setting studied by Burgess and Donaldson (2010, 2012), most notably that trade costs seem if anything to have risen between the tail end of the Colonial period and the start of our sample, 1970. As evidence for this claim, we find that local rainfall shocks affect local prices at the start of our sample period (consistent with substantial barriers to trade across locations), while Donaldson (2008) finds they did not post railway construction in his Colonial India sample (consistent with low barriers to trade across locations).
an alternative quantitative general equilibrium framework that allows us to analyze the trade patterns of a finite number of homogeneous goods (which is perhaps more realistic in an agricultural setting); second, by embedding a portfolio allocation decision into a general equilibrium trade setting, we theoretically characterize the optimal endogenous response of agents to changes in their risk profile resulting from trade liberalization and empirically validate that farmers are indeed responding as predicted; third, our framework yields normative implications for the interaction between trade liberalization and the “complementary” domestic policy of offering farmers better insurance.

We also relate to two strands of the economic development literature. First, we follow a long tradition of modeling agricultural decisions as portfolio allocation problems. For example, Fafchamps (1992) theoretically explores the trade off between cash crop production and food self-sufficiency when production is risky; Rosenzweig and Binswanger (1993) investigates distributional implications of weather risk in rural India; and Kurosaki and Fafchamps (2002) tests for the efficiency of insurance markets in Pakistan by investigating crop choices. Second, there is also a substantial development literature examining the effect that access to formal credit has on farmers, e.g. Burgess and Pande (2005) and Jayachandran (2006). Consistent with both strands of literature, we find that better access to rural banks is correlated with farmers allocating their resources toward more risky portfolios.

The remainder of the paper is organized as follows. In the following section, we describe the empirical context and the data we have assembled. Section 3 presents two new stylized facts relating trade to volatility and the resulting responses by farmers. In section 4, we develop the model, show that it is consistent with the reduced form results, and analytically characterize the second moment welfare effects of trade. In Section 5, we structurally estimate the model and quantify these welfare effects. Section 6 concludes.

2 Empirical context and Data

In this section, we briefly describe the empirical context and the data we have assembled.

2.1 Rural India over the past forty years

This paper focuses on rural India over a forty year period spanning the 1970s through the 2000s. Over this period, there were three major developments that had substantial impacts on the welfare of rural Indians. The first set of changes were to the technology of agricultural production. Increased use of irrigation, with coverage rising from 23 to 49
percent of arable land, reduced the variance of yields by reducing the reliance on rainfall. The use of high-yield varieties (HYV) increased from 9 to 32 percent of arable land—a process dubbed “the green revolution”—raising both mean yields and altering the variance of yields (with the variance falling due to greater resistance to pests and drought, or rising due to greater susceptibility to weather deviations—see Munshi (2004) for further discussion). The second major change was the policy-driven expansion of formal banking into often unprofitable rural areas (see Burgess and Pande (2005) and Fulford (2013)). The availability of credit helped farmers smooth income shocks and so provided a form of insurance.

The third set of changes relates to reductions in inter- and particularly intra-national trade costs. The reductions were driven by two types of policy change. The first, that we will exploit extensively in the empirical analysis, was a major expansion of the Indian inter-State highway system including the construction of the ‘Golden Quadrilateral’ between Mumbai, Chennai, Kolkata and Delhi and the ‘North South and East West Corridors’. The result was that over the sample period, India moved from a country where most freight was shipped by rail to one dominated by roads—in 1970 less than a third of total freight was trucked on roads, four decades later road transport accounted for 64 percent of total freight. The second policy change was the broad economic liberalization program that was started in 1991 that reduced agricultural tariffs with the outside world and began to dismantle the many restrictions to inter-state and inter-district trade within India as documented in Atkin (2013).

2.2 Data

We have assembled a detailed micro-dataset on agricultural production and trade costs covering the entirety of the forty year period discussed above. These datasets come from the following sources:

Crop Choices: Data on cropping patterns, crop prices and crop yields come from the ICRISAT Village Dynamics in South Asia Macro-Meso Database (henceforth VDSA) which is a compilation of various official government datasources. The database covers 15 major crops across 311 districts from the 1966-67 crop year all the way through to

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3Both these figures and the HYV ones below come from the 1970-2009 change in area under irrigation (under HYC crops) among our sample districts in the ICRISAT VDSA data introduced in the next section.

4See Datta (2012); Ghani, Goswami, and Kerr (2014); Asturias, García-Santana, and Ramos (2014) for estimates of the effect of the “Golden Quadrilateral” on firm inventories, manufacturing activity, and firm competition, respectively. Donaldson (2008) documents the effect of railroad investments in Colonial India, while Burgess and Donaldson (2010) and Burgess and Donaldson (2012) explore the impacts of these same railroads on volatility, as measured by the incidence of famine.
the 2009-10 crop year. The dataset covers districts in 19 of India’s states using the 1966 district boundaries to ensure consistency over time.

**Trade Costs:** We obtained the government-produced *Road Map of India* from the years 1962, 1969, 1977, 1988, 1996, 2004 and 2011. The maps were digitized, geo-coded, and the location of highways identified using an algorithm based on the color of digitized pixels. Figure 1 depicts the evolution of the Indian highway system across these years; as is evident, there was a substantial expansion of the network over the forty year period. Using these maps, we construct a “speed image” of India, assigning a speed of 60 miles per hour on highways and 20 miles per hour elsewhere and use the Fast Marching Method (see Sethian (1999)) to calculate travel times between any two points in India.

**Non-Agricultural Wages and Employment Shares:** Wage rates and population counts broken by agricultural and on-agricultural work are drawn from the VDSA database.

**Rural Bank Data:** Data on rural bank access, an important insurance instrument in India, come from RBI bank openings by district assembled by Fulford (2013).

**Agricultural Technology:** The area under irrigation and the area planted with HYV crops is drawn from the VDSA database.

**Consumer Preferences:** Consumption data come from the National Sample Survey (NSS) Schedule 1.0 Consumption Surveys produced by the Central Statistical Organization.

**Rainfall Data:** Gridded weather data come from Willmott and Matsuura (2012) and were matched to each district by taking the inverse distance weighted average of all the grid points within the Indian subcontinent.

### 3 Trade and Volatility: Stylized Facts

In this section, we provide two sets of stylized facts that suggest second-moment trade effects may be important in our context. First, we provide evidence for what will be the central link between trade costs and volatility in our theoretical model: we show that reductions in trade costs have reduced the correlation between prices and quantities thereby raising total revenue volatility for farmers. Second, we provide evidence for the portfolio choice model that plays a key role in understanding the second-moment effects of trade and will later allow us to measure farmer’s risk aversion: we show that reductions in trade costs have led farmers to move into crops with higher means (a first-order effect)

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5The 15 crops are barley, chickpea, cotton, finger millet, groundnut, linseed, maize, pearl millet, pigeon pea, rice, rape and mustard seed, sesame, sorghum, sugarcane, and wheat. These 15 crops accounted for an average of 73 percent of total cropped area across districts and years.

6See Allen and Arkolakis (2014) for a previous application of the Fast Marching Method to estimate trade costs.
and less risky yields (a second-order effect).

3.1 Volatility, the correlation of prices and yields and trade costs

Stylized Fact 1A: the negative covariance between price and yields has reduced in magnitude over time

Figure 2 plots the variance of logged agricultural revenues per hectare across our 311 sample districts for each decade between the 1970s and 2000s, labeled “Total Revenue Volatility”. While the rise in volatility is consistent with the second moment effects of trade barrier reductions, given the myriad of changes over this period detailed in Section 2.1, it is valuable to decompose the rise into its constituent parts.

With many potential crop choices the variance is a function of the covariances between prices as yields both within and across crops. It can be shown that the variance of log revenue can be decomposed into three terms: the variance of log prices, the variance of log revenue, and the covariance between log prices and log revenue:

$$\text{var} (\ln R_i) = \bar{\theta}_i^p \Sigma_i^{p,p} \bar{\theta}_i + \bar{\theta}_i^y \Sigma_i^{y,y} \bar{\theta}_i + 2 \bar{\theta}_i^p \Sigma_i^{p,y} \bar{\theta}_i + \varepsilon_i,$$

where $\bar{\theta}_i$ is a $G \times 1$ vector of land allocation shares for each good $g$, $\Sigma_i^{y,y}$ and $\Sigma_i^{p,p}$ are $2G \times 2G$ variance covariance matrices for yields $y$ and prices $p$, $\varepsilon_i$ is the residual resulting from a second order Taylor approximation.\(^7\)

The contribution of each of these terms—price variability $(\bar{\theta}_i^p \Sigma_i^{p,p} \bar{\theta}_i)$, yield variability $(\bar{\theta}_i^y \Sigma_i^{y,y} \bar{\theta}_i)$, the covariance between prices and yields $(2 \bar{\theta}_i^p \Sigma_i^{p,y} \bar{\theta}_i)$, and the approximation error—is plotted alongside the total variance in Figure 2. Although the price and yield volatility terms show non-monotonic patterns over time, the covariance term shows a monotonic increase from large to small negative values: prices rise in response to low yield realizations, but less so over time. This lack of responsiveness to local productivity shocks with trade is precisely the channel through which second moment effects manifest themselves in Newbery and Stiglitz (1984).\(^8\)

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\(^7\) We hold the crop area fixed across states as planting decisions must be made before the state is realized and assume that prices and yields are log normally distributed:

$$\begin{pmatrix} \ln p_i \\ \ln y_i \end{pmatrix} \sim N \left( \begin{pmatrix} \mu_p \\ \mu_y \end{pmatrix}, \begin{pmatrix} \Sigma_i^{p,p} & \Sigma_i^{p,y} \\ \Sigma_i^{y,p} & \Sigma_i^{y,y} \end{pmatrix} \right).$$

\(^8\) Of course, there are two major caveats in making inferences about welfare from these findings. First, we are decomposing revenue not profit volatility, and crop costs may be changing over time—an issue we confront head on in the structural estimates. Second, although the revenues are adjusted by the all-India CPI, they are not real in the sense that we do not adjust for changes in the local price index—changes which will be accounted for in the structural estimates and which play an important role in the Pareto inferiority
Stylized Fact 1B: the correlation between price and yields declines with market access

While these reductions in the covariance term are consistent with reduction in trade costs, we now turn to establishing a direct link. To do so, we explore district-decade level variation in trade costs. In order to purge the variance and covariance terms from changes in mean prices and mean yields, we focus on scale-invariant measures, the coefficient of variation of revenue, prices and yields, and the correlation between prices and yields. (Appendix Figure 9 shows these substantial changes in means.) We regress each of these terms (at the district-decade level) on measures of trade openness that draw on the digitized road maps described in Section 2.2. Recall the digitized maps allow us calculate the bilateral travel time between any two points in India. Similarly to Donaldson and Hornbeck (2013), we construct a market access measure for district $i$ by taking a weighted sum of the (inverse) bilateral travel times to each of the $J$ other districts as follows:

$$ MA_{it} = \sum_{j} \left( \frac{1}{\text{travel time}_{ij}} \right)^{\phi} Y_{jt} $$

where $Y_{jt}$ is the income of district $j$ in period $t$ (proxied by the total agricultural revenues in our dataset) and $\phi > 0$ determines how quickly market access declines with increases in travel times. Higher values of market access correspond to greater trade openness as districts are able to trade more cheaply with districts where demand is high. To parametrize $\phi$ we draw on the gravity literature that regresses log trade flows on log distance to estimate how quickly trade flows decline with distance. Drawing on the meta-analysis Head and Mayer (2014) and Disdier and Head (2008), we set $\phi = 1.5$, the average gravity coefficient for developing country samples, in our preferred market access specification.\(^9\) We also consider $\phi = 1$, a natural benchmark and close to the average of 1.1 found for the all country sample; population (rather than revenue) weighted measures; and alternate estimates of the off-highway speed of travel ($1/4$ of that on the highway rather than $1/3$) for robustness.

The regressions are shown in Table 1. Each cell is the coefficient from a single regression of one of the three scale-invariant components of revenue volatility (or revenue itself) at the district-decade level on one of the market access measures described above (district-decade averages of the baseline measure, the measure using $\phi = 1$, a population result of Newbery and Stiglitz (1984).

\(^9\)Head and Mayer (2014) perform a meta-analysis of gravity estimates in the literature report and report an average coefficient on log distance of -1.1 across 159 papers and 2,508 regressions. Head and Mayer (2014) builds off an earlier meta-analysis by Disdier and Head (2008) regresses 1,467 estimates from the literature on characteristics of the underlying specifications. They find estimates based on developing country samples are higher by an average of 0.44 (column 4 of Table 2 in Disdier and Head (2008)) consistent with distance being more costly in developing countries as found in Atkin and Donaldson (2015).
weighted measure, and a measure with the slower off-highway speed). The even columns also include district fixed effects (and hence identify off differences within districts over time) while the odd numbered columns include decade fixed effects in addition to the district ones (and hence identify off difference within districts over time controlling for trends using time changes in other districts). When considering the correlation between prices and yields, the coefficients on the market access variable are positive and significant for both fixed effect specifications and the three market access measures. In contrast, the coefficient of variation of yields is unrelated and that of prices only weakly related to reductions in trade costs.

While the correlation between price and yields is informative, we now explore the relationship between trade costs and the elasticity of local prices to yields, an alternative scale-invariant measure where confounding factors can be controlled for. To do so, we estimate

$$\ln p_{igt\delta} = \beta_{igd} \ln y_{igt} + \delta_{igd} + \delta_{itd} + \delta_{gtd} + \nu_{igt\delta},$$

where $\ln p_{igt\delta}$ is the observed local price in district $i$ of good $g$ in year $t$ in decade $d$, $\ln y_{igt}$ is the observed yield, and $\beta_{igd}$ is the elasticity. We include three sets of fixed effects: a district-crop-decade fixed effect to control for changes in the area allocated to the crop, preference changes or changes in crop-specific costs; a district-year fixed effect that controls for the aggregate income of the district in that year; and a crop-year fixed effect that controls for changes in the world price of the good. Identification of $\beta_{igd}$ can be achieved via ordinary least squares as long as the variation in the yields of good $g$ in district $i$ in time $t$ is uncorrelated with the residual.\textsuperscript{10} Since it may be the case that more open locations have better access to inputs like fertilizer, we also instrument for the yield using local variation in rainfall. Table 2 regresses these crop-decade-district specific elasticities on the four sets of market access measures as well as crop-decade and crop-district fixed effects. As found for the correlation, the elasticity of local prices to local yields increased significantly (from negative values towards zero) with improvements in any of the four measures of market access.

In summary, we find a weakening of the inverse relationship between prices and yields as trade costs fell, consistent with the conjecture that reductions in trade costs increased revenue volatility through changes in the covariance between price and yields.

\textsuperscript{10}This is valid under the joint assumption that location $i$ is small (so that its yield does not affect the world price) and the yield is uncorrelated with the within-state variation in trade openness.
3.2 Crop choices and trade costs

Stylized Fact 2A: Crop choice responds to the mean and variance of the yield

Crops such as chickpea, cotton, rice and wheat have very different mean yields, and there is also substantial variation within crops across regions of India and across time. The variance of yields also varies dramatically across crops, districts and time. Just as important as the variances are the covariances of yields across crops as these covariances allow farmers to hedge production risk in one crop by planting another crop that holds up well under the agroclimatic or pest conditions under which the first crop fails. Figures 10, 11, and 12 in the Appendix provide examples of variation in means, variances, covariances, and crop choice across decades and districts.

Farmers’ respond to these different means, variances and covariances in the ways modern portfolio theory would predict. Column 1 of Table 3 regresses crop choice ($\theta_{igd}$, the average fraction of the total area allocated to a particular district-crop-decade combination) on measures of the mean and variance of that crops yield (the log mean yield, $\log \mu_{igd}$, and the log variance of yield for that district-crop-decade, $\log \sigma_{igd}^2$):

$$\theta_{igd} = \beta_1 \log \mu_{igd} + \beta_2 \log \sigma_{igd}^2 + \gamma_{gd} + \gamma_{id} + \gamma_{ig} + \epsilon_{igd}$$

We saturate the model by including crop-decade, district-decade, and district-crop fixed effects. As crop choices are not independent, all standard errors are clustered at the district-decade level.

Consistent with farmers being risk averse, farmers allocated a significantly larger fraction of their farmland to crops that had high mean yields and, conditional on the mean yield, a significantly smaller amount to crops with a high variance of yields.

Stylized Fact 2B: Farmers moved into less risky portfolios where market access changed most

We now show that the farmers’ crop choices introduced in the previous steps responded to the reductions in trade costs (and corresponding increases in market access) introduced in Stylized Fact 1B. To do so, we interact both the log mean yield and the log variance of yield with our market access measures (with the main effect of the market access measure is swept out by the district-decade fixed effects):

$$\theta_{igd} = \beta_1 \log \mu_{igd} + \beta_2 \log \sigma_{igd}^2 + \beta_3 \log \mu_{igd} \times MA_{id} + \beta_4 \log \sigma_{igd} \times MA_{id} + \gamma_{gd} + \gamma_{id} + \gamma_{ig} + \epsilon_{igd}$$

The regression coefficients are shown in column 2 of Table 3. We find a significant positive $\beta_3$ coefficient and a significant negative $\beta_4$ coefficient. Reductions in trade costs, and hence increased market access, led farmers to further increase their land allocation.
to high yield crops and further reduce their land allocation to high variance crops. These findings are consistent with farmers responding to the reduced responsiveness of price to yields highlighted in the previous section (and the resulting reduction in the in the insurance provided by price movements) by moving into less risky crop allocations (a second-moment effect). The increased loading on the mean yield is consistent with farmers increased specialization that greater market access allows (a first-moment effect). Similar and significant results obtain for the three other market access measures described in Section 3.1 and are shown in columns 4, 6 and 8.

**Stylized Fact 2C: The movement into less risky portfolios is attenuated by bank access**

Finally, we take the previous specification and include an additional set of interactions with the number of banks per capita in that district. As discussed in Section 2.1, the presence of banks provides a form of insurance as farmers can take out loans in bad times and repay them in good times. These triple interactions are shown in columns 3, 5, 7 and 9 of Table 3. The triple interaction of log variance of yields, banks and market access is positive and significantly different from zero using all four market access measures. Consistent with farmers being willing to bear more risk if insured, the presence of more insurance options attenuated the move into less risky crops that resulted from reductions in trade costs.

### 4 Modeling trade and volatility

In this section, we develop a quantitative general equilibrium model of trade and volatility. To do so, we first develop a many country Ricardian trade model with a finite number of homogenous goods and arbitrary (symmetric) bilateral trade costs. We circumvent familiar issues due to corner solutions by assuming that there are many (infinitesimal) traders, each of whom has a distinct iceberg trade cost drawn from a Pareto distribution. This assumption yields a tractable equation for the equilibrium prices in each location and an analytical expression for the equilibrium pattern of specialization across countries that depends only on exogenous parameters. This framework admits a straightforward way of incorporating volatility. By applying tools from the portfolio allocation literature, we derive tractable expressions for the equilibrium pattern of specialization across countries; in particular, we show that the entire model remains sufficiently tractable to yield both qualitative predictions that are consistent with the stylized facts above and structural estimating equations that allow us to quantify the role of volatility in trade below.
4.1 Model setup

We begin by describing the setup of the model.

Geography

The world is composed of a large number of locations (indexed by $i$) separated by trade costs. Each location $i$ is inhabited by a measure $M_i$ of identical farmers, who produce and consume goods in location $i$, and a large number of heterogeneous traders, who engage in arbitrage. We describe both the farmers and the traders behavior in more detail below.

Production

There are a finite number of $G$ homogenous goods (indexed by $g$) that can be produced in each location $i$. In what follows, we will refer to good $g = 1$ as a “non-agricultural” good and goods $g > 1$ as “crops.” Labor is the only factor of production. Each farmer in each location is endowed with a unit of time and chooses how to allocate her time across the production of each of the $G$ goods. Let $\theta_{f ig}$ denote the fraction of time farmer $f$ living in location $i$ allocates to good $g$.

Production is risky. In particular, let the (exogenous) productivity, the “yield”, of a unit of labor in location $i$ for good $g$ be $y_{ig}(s)$, where $s \in S$ is the state of the world. We abstract from idiosyncratic risk and assume that all farmers within a given location in a particular state of the world face the same yields for all goods.\footnote{An alternative interpretation that is mathematically equivalent is to assume that farmers face idiosyncratic risk but engage in a perfect risk sharing arrangement with other farmers in the same location as in the perfect insurance model of Townsend (1994).} Given her time allocation, the nominal income farmer $f$ receives in state $s \in S$ is:

$$Y_{fi}(s) = \sum_{g=1}^{G} \theta_{f ig} y_{ig}(s) p_{ig}(s),$$  

where $p_{ig}(s)$ be the price of good $g$ in location $i$ in state $s$ (which will be determined in equilibrium below).

Preferences

Farmers receive utility $U_{fi}(s)$ in state $s$ where the utility function displays constant relative risk aversion governed by parameter $\rho > 0$ and an inner constant elasticity of substitution (CES) nest across goods:

$$U_{fi}(s) \equiv \frac{1}{1-\rho} \left( \left( \sum_{g=1}^{G} \frac{1}{\sigma} c_{f ig}(s)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \right)^{1-\rho},$$  

(3)
where \( c_{fgi}(s) \) denotes the quantity consumed of good \( g \) in state \( s \) and \( \alpha_{ig} > 0, \sum_{g=1}^{G} \alpha_{ig} = 1 \) is a demand shifter for good \( g \). The corresponding indirect utility function is:

\[
U_{fi}(s) = \frac{1}{1 - \rho} \left( \frac{Y_{fi}(s)}{\left( \sum_{h=1}^{G} \alpha_{ih} p_{ih}(s) \right)^{1-\sigma}} \right)^{1-\rho}.
\]  

(4)

**Trade**

There exists a continuum of traders inhabiting each location \( i \). For every (infinitesimal) unit of good \( g \) that a farmer wishes to purchase or sell, she is randomly matched to a trader and transacts with the trader at the local market price \( p_{ig}(s) \). The trader simultaneously engages in price arbitrage across locations: if the farmer wants to purchase the good \( g \) from the trader, the trader decides from which market to source the good; conversely, if the farmer wants to sell the good \( g \) to the trader, the trader decides to which market he will sell.\(^{12}\)

A trader incurs a bilateral iceberg trade cost from either purchasing or selling a good from another market. We assume that traders are heterogenous in the iceberg bilateral trade costs they face. In particular, the probability that a randomly matched trader is able to purchase a unit of good from \( i \) and sell it to \( j \) (or vice versa) with an bilateral iceberg trade cost less than \( \bar{\tau} \) is Pareto distributed with shape parameter \( \varepsilon_{ij} \in [0, \infty) \):

\[
\Pr \{ \tau_{ij} \leq \bar{\tau} \} = 1 - \bar{\tau}^{-\varepsilon_{ij}},
\]

where \( \varepsilon_{ij} = \varepsilon_{ji} \). Note that the greater the value of \( \varepsilon_{ij} \), the lower the bilateral trade costs (in particular, \( \varepsilon_{ij} = 0 \) indicates that trade is infinitely costly and as \( \varepsilon_{ij} \to \infty \) trade becomes costless).\(^{13}\)

In what follows, we assume that bilateral trade costs are identical across goods and independently distributed across destinations (e.g. a trader having a low trade cost to one destination does not change the probability he will have a low trade cost to another destination).\(^{14}\)

\(^{12}\)This mechanism through which farmers must sell all their output via traders mimics agricultural marketing boards that are present in many developing countries, including India. The Agricultural Produce Marketing Committee Act mandates that Indian farmers must sell exclusively through government-authorized traders.

\(^{13}\)While the limit of the model as epsilon goes to infinity is well defined, note that it does not converge to the costless trade Ricardian equilibrium, as we assume that traders who are indifferent will always transact locally. Since the probability of being indifferent is zero for any finite \( \varepsilon \), this does not affect the results that follow.

\(^{14}\)An alternative narrative that is mathematically equivalent to this setup is that there exists a single representative trader who for each unit transacted draws a bilateral trade cost from the same distribution, i.e., in what follows it does not matter if there is a random bilateral trade cost and a single trader or a distribution of bilateral trade costs across many traders and random matching between farmers and traders.
4.2 Trade and equilibrium prices

We first solve for equilibrium prices in a given state of the world given crop choices. The CES preferences imply that in equilibrium, the total expenditure on good $g$ in location $i$ at price $p_{ig}(s)$ will be:

$$p_{ig}(s)C_{ig}(s) = \frac{\alpha_{ig}(p_{ig}(s))^{1-\sigma}}{\sum_h \alpha_{ih}(p_{ih}(s))^{1-\sigma}} Y_i(s),$$  

(5)

where $C_{ig}(s) = M_i c_{fig}(s)$ is the total quantity of $g$ consumed in a location $i$ and $Y_i(s) = M_i Y_{fi}(s)$ is the total income in location $i$. On the production side, $Q_{ig}(s) = M_i \theta_{ig} y_{ig}(s)$ is the total quantity produced of good $g$ in location $i$.

We now consider how the arbitrage behavior of traders affects the relationship between the production and consumption in a location. In equilibrium, it must be the case that the quantity consumed of good $g$ in location $i$ that is also produced in location $i$ must be equal to quantity produced of good $g$ in location $i$ that is also consumed in location $i$:

$$C_{ig}(s) \times \Pr\{\text{sourcing locally is cheapest}\} = Q_{ig}(s) \times \Pr\{\text{selling locally is most profitable}\}$$

(6)

By the law of large numbers, the fraction of the quantity consumed of good $g$ in location $i$ that is also produced in location $i$ is equal to the probability that it is cheaper to purchase good $g$ locally than to import it from any other location, i.e.:

$$\Pr\{\text{sourcing locally is cheapest}\} = \Pr\left\{ p_{ig}(s) \leq \min_{j \neq i} \tau_{ji} p_{jg}(s) \right\} \iff \prod_{j \neq i} \left( \left( \frac{p_{jg}(s)}{p_{ig}(s)} \right)^{\epsilon_{ji}} \right) ^{\mathbb{1}\{p_{jg}(s) \geq p_{ig}(s)\}},$$

(7)

where $\mathbb{1}\{\cdot\}$ is an indicator function and the second line imposes the Pareto distribution and the assumption that the realization of trade costs are independent across origins. Similarly, the fraction of the quantity produced of good $g$ in location $i$ that is also sold in location $i$ is equal to the probability that the local price is greater than the price the trader would receive if he were to export it to any other location, i.e.:

$$\Pr\{\text{selling locally is most profitable}\} = \Pr\left\{ p_{ig}(s) \geq \max_{j \neq i} \frac{p_{jg}(s)}{\tau_{ij}} \right\} \iff \prod_{j \neq i} \left( \left( \frac{p_{jg}(s)}{p_{ig}(s)} \right)^{\epsilon_{ij}} \right) ^{\mathbb{1}\{p_{jg}(s) \geq p_{ig}(s)\}}$$

(8)

Together, equations (6), (7), and (8) along with symmetric bilateral distributions imply
that the ratio of local consumption and production is the product of the ratio of the local price to prices elsewhere:

\[ \frac{C_{ig}(s)}{Q_{ig}(s)} = \prod_{j \neq i} \left( \frac{p_{ig}(s)}{p_{ij}(s)} \right)^{\varepsilon_{ij}}. \]  

(9)

Substituting the demand equation (5) for \( C_{ig}(s) \) and the production equation for \( Q_{ig}(s) \) into equation (9) we obtain:

\[ p_{ig}(s) = \left( \left( \frac{\alpha_{ig}}{\theta_{ig}y_{ig}(s)} \sum_h \alpha_{ih} \left( p_{ih}(s) \right)^{1-\sigma} \right) \left( \prod_{j \neq i} p_{ij}(s)^{\varepsilon_{ij}} \right) \right)^{\frac{1}{\sigma + \sum_k \varepsilon_{ik}}}. \]  

(10)

We can further express the equilibrium price in location \( i \) as a function of the realized yields in all locations. Define \( E \) to be the \( N \times N \) matrix with \( E_{ij} = -\varepsilon_{ij} \) for \( i \neq j \) and \( E_{ii} = \sigma + \sum_{k \neq i} \varepsilon_{ik} \) for all \( i \in \{1, \ldots, N\} \). Define \( T \equiv E^{-1} \). Then by taking logs of equation (10) and solving the resulting system of equations for equilibrium prices we have:

\[ p_{ig}(s) = \prod_{j=1}^{N} \left( D_{j}(s) \left( \frac{\alpha_{ij}}{\theta_{ij}y_{ij}(s)} \right) \right)^{T_{ij}}, \]  

(11)

where \( D_{j}(s) \equiv Y_{j}(s) P_{j}(s)^{\sigma-1} \) is aggregate demand. Equation (11) implies that the elasticity of the price of good \( g \) in location \( i \) to the yield in location \( j \) (conditional on the good invariant constant \( D_{j}(s) \)) is \( T_{ij} \), which depends only on the elasticity of substitution and the set of bilateral trade costs shape parameters \( \varepsilon_{ij} \).

### 4.3 Special case: no volatility

Prior to discussing the general case where yields are stochastic, it is informative to consider the simpler case where yields are deterministic. In this case, we show that the equilibrium crop choice takes a very simple analytical form.

In the absence of uncertainty, the return to the producer per unit of time (i.e. her factor price) must be equalized across all goods she produces\(^{15}\), i.e.:

\[ p_{ig}y_{ig} = p_{ih}y_{ih} \quad \forall g, h \in \{1, \ldots, G\}. \]

Taking logs and substituting in equation (11) for the equilibrium price yields:

\[ \sum_{j=1}^{N} T_{ij} \ln \left( \frac{\alpha_{ij}}{\theta_{ij}y_{ij}(s)} \right) + \ln y_{ig} = \sum_{j=1}^{N} T_{ij} \ln \left( \frac{\alpha_{jh}}{\theta_{jh}y_{jh}(s)} \right) + \ln y_{hg} \equiv \kappa_{i} \]

for some \( \kappa_{i} \in \mathbb{R} \). This can be written in vector notation as a system of equations across all

\(^{15}\text{It is straightforward to show that in equilibrium, all goods will be produced in all locations, as equation (11) implies that the price of a good will go to infinity as the time allocated to that good goes to zero.}\)
locations as follows:

\[
\{\ln y_{ig} - \kappa_i\}_i = T \left\{ \ln \left( \frac{\theta_iy_{ig}(s)}{\alpha_{ig}} \right) \right\}_i \iff \\
\{\ln \left( \frac{\theta_iy_{ig}(s)}{\alpha_{ig}} \right) \right\}_i = T^{-1} \{\ln y_{ig} - \kappa_i\}_i,
\]

where \(\{x_i\}_i\) indicates the \(N \times 1\) vector with \(i^{th}\) element \(x_i\). Recall that \(T^{-1} = E\), where \(E_{ij} = -\varepsilon_{ij}\) for \(i \neq j\) and \(E_{ii} = \sigma + \sum_{k \neq i} \varepsilon_{ik}\), which yields the following solution to the system of equations:

\[
\theta_i \propto \alpha_{ig}^{\sigma-1} \prod_{j \neq i} (y_{ig}/y_{jg})^{\varepsilon_{ij}}. \tag{12}
\]

where \(\tilde{\kappa}_i \equiv (\sigma + \sum_{j \neq i} \varepsilon_{ij}) \kappa_i - \sum_{j \neq i} \varepsilon_{ij} \kappa_j\). Combining the time constraint \(\sum_{g=1}^G \theta_{ig} = 1\) and equation (12) yields:

\[
\theta_{ig} = \frac{\alpha_{ig} (y_{ig})^{\sigma-1} \prod_{j \neq i} (y_{ig}/y_{jg})^{\varepsilon_{ij}}}{\sum_{h=1}^G \alpha_{ih} (y_{ih})^{\sigma-1} \prod_{j \neq i} (y_{ih}/y_{jh})^{\varepsilon_{ij}}} \tag{13}
\]

To our knowledge, equation (13) is the first analytical characterization of the equilibrium pattern of specialization in a Ricardian trade model with many countries separated by arbitrary trade costs who trade a finite number of homogeneous goods. All else equal, a country will specialize more in the production of good \(g\) the greater its own demand for that good (the \(\alpha_{ig}\) term), the greater its productivity of that good (the \(y_{ig}\) term) and the greater its comparative advantage in that good (the \(\prod_{j \neq i} (y_{ig}/y_{jg})^{\varepsilon_{ij}}\) term), all relative to those same terms for all other goods. The greater the Pareto shape parameter \(\varepsilon_{ij}\) governing the distribution of bilateral trade costs between \(i\) and \(j\) (i.e. the lower the bilateral trade costs), the greater the weight the relative productivity of \(i\) and \(j\) matters for \(i\)'s specialization.

It is important to emphasize that equation (13) characterizes the pattern of specialization across countries solely as a function of exogenous model parameters. Since the pattern of specialization in Ricardian models depends on differences in (endogenous) factor prices across countries (e.g. wages), a natural question is why these factor prices do not appear.

\[\text{16}\text{Other papers who have characterized the patterns of trade in a many-country Ricardian model include the seminal paper of Eaton and Kortum (2002), who rely on a distribution of productivities across goods and Allen (2014), who relies on a random search process. In contrast, to derive an analytical expression here for a finite number of goods, we rely on a distribution of bilateral trade costs for a single good.}\]
in the expression. A ramification of the bilateral trade costs being distributed Pareto is that the elasticity of the price of any good \( g \) (relative to any other good \( h \)) in any location \( i \) to changes in the allocation of good \( g \) in any other country \( j \) is constant—i.e. \( \frac{\partial \ln \frac{p_i g}{p_i h}}{\partial \ln \theta_{jg}} = -T_{ijg} \) (see equation 11)—and in particular does not depend on the endogenous aggregate demand of location \( j \).\(^{17}\) Because a producer’s decision of what to produce depends only on the relative returns across different goods, this result allows us to analytically solve the pattern of specialization across all locations simultaneously while accounting for the effect of changes in specialization on prices.

What about the gains from trade? Given that factor prices are equalized across all goods, the utility of farmers can be written as:

\[
U_{fi} = \frac{1}{1 - \rho} \left( \frac{y_{ig} p_{ig}}{\left( \sum_{h=1}^{G} \alpha_{ig} p_{ih}^{1-\sigma} \right)^{1-\sigma}} \right)^{1-\rho} \quad \forall g \in \{1, ..., G\}. 
\]

Furthermore, because of the linear production function and the incomplete specialization of producers, the price of any good is equal to its inverse yield times a location specific constant:

\[
p_{ig} = \frac{1}{y_{ig}} y_{i1} p_{i1},
\]

so that utility can be written as:

\[
U_{fi} = \frac{1}{1 - \rho} \left( \sum_{h} \alpha_{ig} y_{ih}^{\sigma-1} \right)^{1-\rho},
\]

i.e. the utility of farmers is *invariant* to the level of trade. Intuitively, as in a standard Ricardian model, opening up to trade increases the returns to goods for which a location has a comparative advantage, causing farmers to reallocate resources to the production of those goods. Unlike a standard Ricardian trade model, however, the presence of heterogeneous trade costs prevents producers from completely specializing, as the price of a good rises without bound as the quantity produced approaches zero; intuitively, for any finite price, some fraction of traders will draw sufficiently high trade costs elsewhere so as to source locally. As a result, reallocation of resources toward the comparative advantage good lowers its price and raises the price of other goods, and equilibrium is achieved when the returns to producing all goods are once again equalized. Because trade does

\(^{17}\)Note that this would not be the case if the distribution of bilateral trade costs differed by good, as then \( \frac{\partial \ln \frac{p_i g}{p_i h}}{\partial \ln \theta_{jg}} = (T_{ijg} - T_{ijg}) \frac{\partial \ln D_j}{\partial \ln \theta_{jg}} - T_{ijg} \), i.e. we would have to account for changes in the aggregate demand \( D_j \) due to the change in specialization in location \( j \).
not affect the relative prices that farmers face nor the income they earn from selling their crops, their welfare is unchanged.

One might (reasonably) wonder where the gains from trade went. The answer is simple: all gains from trade accrue to traders through arbitrage rents. We view this implication as a feature of the model (rather than a problem) as in the empirical context we consider, it seems reasonable to assume that it is the traders rather than farmers who engage in price arbitrage across locations and enjoy the associated rents. For example, since the 1960’s, Agricultural Produce Marketing Committee (APMC) Acts have required farmers sell their output to government-approved traders and it is illegal to transact directly with buyers,\footnote{The central government proposed a modification to the APMC act in 2003 that allows direct selling, but most states have either not yet adopted or not yet implemented these modifications.} and there is a wealth of anecdotal evidence suggesting that these traders accrue large rents.\footnote{See, for example, “The mango’s journey” in The Financial Times, August 4th, 2009, which includes a photo of two traders touching hands under a towel with the caption: ...many deals are actually negotiated secretly, using hand signals hidden from view by a towel, which keeps farmers in the dark about the true price their mangoes are fetching, and allows the traders to increase their margins at the farmers’ expense.}

That being said, the gains from trade accruing to the trader are interesting in their own right—particularly since, to allow for the farmers to gain from trade, we could instead assume that all trader gains were redistributed lump-sum back to farmers.\footnote{In this case, the equilibrium prices and allocation of resources would remain unchanged and given by equations (11) and (13), respectively.}

It is reasonably straightforward to calculate these gains. Let $\pi_{ig}$ be the total arbitrage rents of a trader in location $i$ selling good $g$. We have:

$$\pi_{ig} = \left[ \Pr \left\{ \max_{j \neq i} \left( \frac{p_{jg}}{\tau_{ij}} \right) \geq p_{ig} \right\} \times E \left[ \max_{j \neq i} \left( \frac{p_{jg}}{\tau_{ij}} \right) \mid \max_{j \neq i} \left( \frac{p_{jg}}{\tau_{ij}} \right) \geq p_{ig} \right] - p_{ig} \right] Q_{ig} +$$

$$+ \left[ p_{ig} - \Pr \left\{ \min_{j \neq i} \tau_{ij} p_{jg} \leq p_{ig} \right\} \times E \left[ \min_{j \neq i} \tau_{ij} p_{jg} \mid \min_{j \neq i} \tau_{ij} p_{jg} \leq p_{ig} \right] \right] C_{ig}. \tag{14}$$

Without loss of generality, order countries in ascending order of their prices of good $g$, i.e. $p_{j+1.g} \geq p_{j.g}$. Then one can show that arbitrage profits are:

$$\pi_{ig} = \left[ \sum_{k=i+1}^{N} \left( \frac{\sum_{l=k}^{N} \varepsilon_{il}}{\sum_{l=k}^{N} \varepsilon_{il}} \right) + 1 \right] \left( \prod_{l=k}^{N} p_{lg}^{\varepsilon_{il}} / p_{kg}^{1 + \sum_{l=k}^{N} \varepsilon_{il}} - p_{k+1.g}^{1 + \sum_{l=k}^{N} \varepsilon_{il}} \right) - p_{ig} \right] Q_{ig} +$$

$$+ \left[ p_{ig} - \sum_{k=1}^{i-1} \left( \frac{\sum_{l=0}^{k} \varepsilon_{il}}{1 - \sum_{l=0}^{k} \varepsilon_{il}} \right) \left( \prod_{l=0}^{k} p_{m(g)}^{\varepsilon_{il}} / p_{k+1.g}^{1 + \sum_{l=0}^{k} \varepsilon_{il}} - p_{kg}^{1 + \sum_{l=0}^{k} \varepsilon_{il}} \right) \right] C_{ig}. \tag{14}$$

Loosely speaking, the gains from trade are larger the greater the difference between the local price and prices elsewhere. Given that the equilibrium prices can be written as a
function of model parameters using equations (11) and (13), equation (14) can then be used to calculate the gains from trade solely as a function of model parameters.

4.4 General case: volatility

We now turn to the general case where yields are subject to shocks (e.g. rainfall realizations) which occur after the time allocation decision has been made (e.g. after planting).

The distribution of real incomes

We first derive the equilibrium real returns for each crop as a function of crop choices. In turn, given a distribution of yields across states of the world, goods and locations, we can characterize the distribution of real incomes.

Substituting the equilibrium price in equation (11) and income in equation (2) into the indirect utility function in equation (19), we obtain:

\[ U_{fi}(s) = \frac{1}{1 - \rho} \left( \sum_{s=1}^{G} \theta f_{ig} z_{ig}(s) \right)^{1-\rho}, \]

(15)

where

\[ z_{ig}(s) \equiv \frac{y_{ig}(s) \left( \prod_{j=1}^{N} \left( \frac{\alpha_{ig}}{\theta_{ig}y_{ig}(s)} \right)^{T_{ij}} \right)}{\left( \sum_{h=1}^{G} \alpha_{ih} \left( \prod_{j=1}^{N} \left( \frac{\alpha_{ih}}{\theta_{ih}y_{ih}(s)} \right)^{T_{ij}} \right)^{1-\sigma} \right)^{1-\sigma}} \]

(16)

is the real income per unit of time producing good \( g \) in location \( i \) in state \( s \).

Under the following assumption, we can characterize the (endogenous) joint distribution of real returns across all crops in terms of the (exogenous) joint distribution of yields across all crops and all locations.

Assumption 1 (Log normal distribution of yields). Assume that the joint distributions of yields across goods are log normal within any location \( i \) and are independently distributed across locations. In particular, define \( y_i(s) \) as the \( G \times 1 \) vector of \( y_{ig}(s) \). Then \( \ln y_i \sim N(\bar{\mu}_y, \Sigma^y) \) for all \( i \in \{1, ..., N\} \).²¹

By applying the familiar second-order approximation used in the finance literature—that the sum of log normal variables is itself approximately log normal (see e.g. Campbell and Viceira (2002))—we can show that both the real returns to each crop and the total returns in each location are approximately log normally distributed. We summarize both these results in the following proposition:

²¹We should note that the assumption that the distributions of yields are independent across locations is not crucial for the results that follow but we make it in order to substantially simplify the notation.
Proposition 1. Define $z_i(s)$ as the $G \times 1$ vector of $z_{ig}(s)$. Then the joint distribution of real returns across goods is log-normal, i.e.

$$\ln z_i \sim N \left(\mu_{iz}^2, \Sigma_{iz}^2\right),$$

where:

$$\mu_{iz}^2 \equiv \left(\mu^{iy} - \sum_{j=1}^N T_{ij} \left(\mu^{iy} - \bar{\alpha}_{ij}' \mu^{ij}_y\right)\right) + \bar{c}_i$$

$$\Sigma_{iz}^2 \equiv \left(\mathbf{I} - T_{ii} \left(\mathbf{I}_G - (1\mathbf{G}_{ij})\right)\right) \Sigma^{iy} \left(\mathbf{I} - T_{ii} \left(\mathbf{I}_G - (1\mathbf{G}_{ij})\right)\right)' + \sum_{j \neq i} (T_{ij})^2 \left(\mathbf{I}_G - (1\mathbf{G}_{ij})\right) \Sigma^{jy} \left(\mathbf{I}_G - (1\mathbf{G}_{ij})\right)'$$

$$\bar{c}_i \equiv \left\{\sum_{j=1}^N T_{ij} \ln \left(\frac{\alpha_{ig}}{\bar{\theta}_{ijg}}\right)\right\}_g - \sum_{j=1}^N T_{ij} \sum_{h=1}^G \alpha_{jh} \ln \left(\frac{\alpha_{jh}}{\bar{\theta}_{jh}}\right) + (\sigma - 1) \frac{1}{2} \sum_{j=1}^N T_{ij}^2 \sum_{h=1}^G \alpha_{jh} \left(\Sigma_{jh}^y - \sum_{l=1}^G \Sigma_{jl}^{jy} \alpha_{jl}\right)$$

Furthermore, to a second-order approximation, total real income $Z_{fi}(s) \equiv \sum_{g=1}^G \theta_{fig} z_{ig}(s)$ is also log normally distributed:

$$\ln Z_{fi}(s) \sim N \left(\mu_{Zi}^2, \sigma_{Zi}^2\right),$$

where:

$$\mu_{Zi}^2 \equiv \bar{\theta}_{fi}' \mu_{iz}^2 + \frac{1}{2} \text{diag} \left(\Sigma_{iz}^2\right) - \frac{1}{2} \bar{\theta}_{fi}^2 \Sigma_{iz}^2 \bar{\theta}_{fi}, \quad (17)$$

$$\sigma_{Zi}^2 \equiv \bar{\theta}_{fi}^2 \Sigma_{iz}^2 \bar{\theta}_{fi}, \quad (18)$$

and $\bar{\theta}_{fi}$ is the $G \times 1$ vector whose $g^{th}$ element is $\theta_{fig}$.

Proof. See Appendix A.1. □

Equations (17) and (18) analytically characterize how farmer’s time allocation choices across different goods affect the mean and variance of real returns. Using this key result, we now characterize the optimal time allocation of farmers.

Optimal crop choice

From the second part of Proposition (1), we can calculate the expected utility of a farmer as a function of her time allocation $\bar{\theta}_{fi} \in \Delta^G$:

$$E \left[U_i \left(\bar{\theta}_{fi}\right)\right] = \frac{1}{1 - \rho} \exp \left(\mu_{Zi}^2 \left(\bar{\theta}_{fi}\right) + \frac{1}{2} (1 - \rho) \sigma_{Zi}^2 \left(\bar{\theta}_{fi}\right)\right)^{1-\rho}, \quad (19)$$

where we now explicitly note the dependence of the real mean and variance of returns on time allocations. Because $E \left[Z_{fi}(s; \bar{\theta}_{fi})\right] = \exp \left(\mu_{Zi}^2 \left(\bar{\theta}_{fi}\right) + \frac{1}{2} \sigma_{Zi}^2 \left(\bar{\theta}_{fi}\right)\right)$, equation (19)
implies that farmer $f$ trades off the (log of the) mean of her real income with the variance of her (log) real income, with the exact trade-off governed by the degree of risk aversion $\rho$.

As a result, by maximizing her expected utility, a farmer will choose an allocation on the mean-variance frontier of real returns, where the slope of the mean-variance frontier at her optimal location will be equal to her degree of risk aversion. To see this, note that the optimal time allocation maximizes the following monotonic transformation of equation (19), where we use equations (17) and (18) from Proposition 1 to characterize the mean and variance of returns:

$$\bar{\theta}_{fi} \equiv \arg \max \sum_{g=1}^{G} \theta_{fig} \left( \mu_{ig} + \frac{1}{2} \Sigma_{ss} \right) - \frac{1}{2} \rho \sum_{g=1}^{G} \sum_{h=1}^{G} \Sigma_{gh} \theta_{fig} \theta_{fih} \text{ s.t. } \sum_{g=1}^{G} \theta_{fig} = 1. \tag{20}$$

By taking first order conditions of the Lagrangian associated with equation (20), we have for all $g \in \{1, ..., G\}$:

$$\mu_{ig} + \frac{1}{2} \Sigma_{ss} - \rho \sum_{h=1}^{G} \Sigma_{gh} \theta_{fih} = \lambda_{fi}, \tag{21}$$

where $\lambda$ is the Lagrange multiplier on the constraint $\sum_{g=1}^{G} \theta_{i} = 1$. Equation (21) is intuitive: a good with a high total variance of real returns (i.e. a high $\sum_{h=1}^{G} \Sigma_{gh} \theta_{h}$), must have high average real returns (i.e. a high $\mu_{ig} + \frac{1}{2} \Sigma_{ss}$) to compensate for the additional risk. The trade-off between risk and return is determined by the degree of risk aversion of the farmer, captured by the parameter $\rho$.

Substituting the functional form for $\mu_{ig}$ given in Proposition 1 into the first order conditions of the farmer given in Equation (21) yields the following system of equations relating the equilibrium allocation of resources across all countries and goods:

$$\sum_{j=1}^{N} \epsilon_{ij} T_{ij} \left( \ln (\theta_{jg}) - \sum_{h=1}^{G} a_{jh} \ln (\theta_{jh}) \right) = b_{ig} + \rho \sum_{h=1}^{G} \Sigma_{gh} \theta_{fih} + \lambda_{fi}, \tag{22}$$

where $b_{ig}$ depends only on exogenous model parameters and captures all of the “demand” aspects of the mean (log) real returns that do not depend on crop choice. Inverting equation (22) to solve for the log crop allocation, recalling that $T^{-1} = E$, and taking the exponential of both sides yields the following analytical expression for the equilib-
rium allocation of resources:

\[
\theta_{ig} \propto \exp \left( b_{ig} - \rho \sum_{h=1}^{G} \Sigma_{gh}^{i} \theta_{ih} \right)^{\sigma} \times \prod_{j \neq i} \left( \frac{\exp \left( b_{ij} - \rho \sum_{h=1}^{G} \Sigma_{gh}^{i} \theta_{ih} \right)}{\exp \left( b_{ij} - \rho \sum_{h=1}^{G} \Sigma_{gh}^{j} \theta_{jh} \right)} \right)^{\epsilon_{ij}} .
\]  

(23)

Equation (23) generalizes equation (13) to incorporate production volatility. It states that producers will allocate more resources (i.e. time) to the production of goods for which the demand relative to risk (i.e. \( b_{ig} - \rho \sum_{h=1}^{G} \Sigma_{gh}^{i} \theta_{ih} \)) is greater relative to their trading partners, where trading partners are weighted by the shape parameters \( \epsilon_{ij} \) that govern bilateral trade costs.

4.5 Model extensions

Before turning to the implications of the model, it is useful to consider two extensions.

Farmer cooperative

We assumed above that each farmer took prices as given. Because trade across locations results in a downward sloping demand curve (see equation 11), if farmers account for the effect of their choice of time allocation on prices (e.g. through forming a farmer cooperative), they will be able to increase their real returns. To see this, assume that there is a single “representative farmer” making production decisions in location \( i \). Unlike above, the representative farmer chooses her time allocation incorporating the effect that her choices will have on the mean real (log) returns \( \mu_{ig}^{z} \). It is straightforward to show that the resulting first order conditions are:

\[
\mu_{ig}^{z} + \frac{1}{2} \Sigma_{ig}^{z} + T_{ii} \frac{\alpha_{ig}}{\theta_{ig}} - \rho \sum_{h=1}^{G} \Sigma_{gh}^{i} \theta_{ih} = \lambda_{fi} + T_{ii} \quad \forall g \in \{1, ..., G\} ,
\]  

(24)

which yields the resulting equilibrium “cooperative” crop choice \( \theta_{ig}^{C} \):

\[
\theta_{ig}^{C} \propto \exp \left( b_{ig} + T_{ii} \frac{\alpha_{ig}}{\theta_{ig}} - \rho \sum_{h=1}^{G} \Sigma_{gh}^{i} \theta_{ih} \right)^{\sigma} \times \prod_{j \neq i} \left( \frac{\exp \left( b_{ij} + T_{ii} \frac{\alpha_{ig}}{\theta_{ig}} - \rho \sum_{h=1}^{G} \Sigma_{gh}^{i} \theta_{ih} \right)}{\exp \left( b_{ij} + T_{jj} \frac{\alpha_{ig}}{\theta_{ig}} - \rho \sum_{h=1}^{G} \Sigma_{gh}^{j} \theta_{jh} \right)} \right)^{\epsilon_{ij}} .
\]  

(25)

Comparing equation (25) to equation (23), the inclusion of the term \( T_{ii} \frac{\alpha_{ig}}{\theta_{ig}} \) indicates that farmers who incorporate the effect of their crop choice on prices allocate more resources toward crops which they demand more highly (i.e. those with greater \( \alpha_{ig} \)). Intuitively, because farmers face a downward sloping world demand curve for their goods, cooperative farmers would want to act like monopolists, restricting the quantity of goods they exchange in order to obtain higher prices.
Imperfect insurance

The model can be easily extended to incorporate insurance, which allows producers to smooth their income after the shocks have occurred. To do so, we make farmers’ consumption a Cobb-Douglas aggregate of their realized real income (i.e. their income with no insurance) and the expected value of their realized real income (i.e. their income with perfect insurance). Farmer utility in state \( s \) is then:

\[
U_{i}^{\text{ins}}(s; \vec{\theta}_{fi}) = \frac{1}{1 - \rho} \left( \kappa_{i} Z_{fi}(s; \vec{\theta}_{fi})^{1 - \chi_{i}} \left( E \left[ Z_{fi}(s; \vec{\theta}_{fi}) \right] \right)^{\chi_{i}} \right)^{1 - \rho},
\]

where \( \chi_{i} \in [0, 1] \) indicates the level of insurance ranging from perfect, \( \chi_{i} = 1 \), to zero, \( \chi_{i} = 0 \), and \( \kappa_{i} \equiv \frac{E[Z_{fi}(s)]^{1 - \chi_{i}}}{E[Z_{fi}(s)]^{1 - \chi_{i}}} \) is a scalar that ensures that mean income is unchanged. In Appendix A.2, we show this formulation for insurance has a straightforward micro-founded interpretation where farmers optimally purchase insurance from (perfectly-competitive) lenders who are less risk averse than the farmers; in this interpretation, \( 1 - \chi_{i} \) is the ratio of the risk aversion of the lenders to the farmers (so in the extreme where the lenders are risk neutral, the farmers are perfectly insured).

Given the results from Proposition 1, expected utility with insurance can be written as:

\[
E \left[ U_{i}^{\text{ins}}(s; \vec{\theta}_{fi}) \right] = \frac{1}{1 - \rho} \exp \left( \sum_{g=1}^{G} \theta_{fg} \left( \mu_{iz}^{g} + \frac{1}{2} \Sigma_{sg}^{g} \right) - \frac{1}{2} \psi_{i} \sum_{g=1}^{G} \sum_{h=1}^{G} \Sigma_{gh}^{g} \theta_{fg} \theta_{fh} \right) \left( 1 - \rho \right),
\]

where \( \psi_{i} \equiv \rho \left( 1 - \chi_{i}(\chi_{i}-2)(\rho-2)-1 \right) \) is a sufficient statistic for the altered trade off between risk and return and is a combination of both the level of risk aversion as previously and now also the extent of insurance to which the farmer has access. (Note that with perfect insurance, \( \psi_{i} = 0 \) and with no insurance, \( \psi_{i} = \rho \)). As above, the farmer chooses her time allocation to maximize her expected utility, yielding the following first order conditions:

\[
\mu_{iz}^{g} + \frac{1}{2} \Sigma_{sg}^{g} - \psi_{i} \sum_{h=1}^{G} \Sigma_{gh}^{g} \theta_{fih} = \lambda_{fi} \quad \forall g \in \{1, \ldots, G\}.
\]

(27)

Comparing these first order conditions to those without insurance in equation (21) above, access to better insurance (i.e. a lower \( \psi_{i} \)) makes farmers act as if they are less risk averse. In what follows, we replace the risk aversion parameter \( \rho \) with this sufficient statistic \( \psi_{i} \) to emphasize that the results are robust to incorporating insurance in this manner.
4.6 Qualitative implications

We now turn to the qualitative implications of the model. We first discuss how the model is consistent with the stylized facts presented in Section 3. We then document two somewhat surprising results: first, in the presence of volatility, opening up to trade can reduce farmer welfare; second, in the presence of trade, offering farmers better insurance can reduce their welfare.

Explaining the stylized facts

Stylized Fact #1 and #2 correspond to the equilibrium pricing equation (11) and the equilibrium time allocation equation (23), respectively. Equation (11) states that the elasticity of the local price to the local yield, i.e. $-\frac{\partial \ln p_{ig}(s)}{\partial \ln y_{ig}(s)}$, is $T_{ii}$, which is decreasing with trade openness.\(^{24}\) Hence as trade costs fall over time (Fact 1A) or with the expansion of the Indian highway network (Fact 1B), local prices will respond less negatively to local yields.

Consistent with Fact 2A, equation (23) states that, all else equal, a farmer will allocate more time toward a crop with a greater average yield (which corresponds to a greater $b_{ig}$) and less time toward a crop with a greater variance (which corresponds to a higher $\sum_{h=1}^{G} \Sigma_{gh}^{iz} \theta_{ih}$). Furthermore, note from footnote 23 that $\frac{\partial b_{ig}}{\partial u_{ig}} = (1 - T_{ii})$, so as trade costs fall (i.e. $T_{ii}$ falls) farmers reallocate their time toward crops with higher means; intuitively, this occurs because the local price falls less for high yield crops as trade costs fall. Similarly, from Proposition 1, as $T_{ii}$ falls, the covariance of real returns $\Sigma_{gh}^{iz}$ becomes more responsive to the covariance of yields $\Sigma_{gh}^{iy}$, causing farmers to reallocate away from crops with high yield volatility as local price movements now offer less insurance against yield shocks. These two predictions comprise Fact 2B. Finally, given the imperfect insurance extension from Section 4.5, if locations with access to banks have lower $\psi_i$, equation (23) implies that farmers will place greater weight on achieving higher mean returns (i.e. greater $b_{ig}$) and less weight on a lower variance of real returns (i.e. $\sum_{h=1}^{G} \Sigma_{gh}^{iz} \theta_{ih}$), consistent with Fact 2C.

Trade may make farmers worse off

In the presence of volatility, relative prices are no longer determined by relative yields as farmers are concerned about both their average returns and the variance of their mean returns. Unlike in the special (deterministic) case considered in Section 4.3, opening up to trade can affect the welfare of farmers through both standard first moment gains from specialization and also through second moment volatility effects.

How volatility affects the farmer’s gains from trade depends on the model parameters.

\(^{24}\)In particular, it is straightforward to show that $T_{ii} = \frac{1}{\sigma}$ in autarky when $\epsilon_{ij} = 0$ for all $i \neq j$ and $T_{ii}$ approaches zero as trade becomes less and less costly, i.e. $\lim_{\min \epsilon_{ij} \to \infty} T_{ii} = 0$. 

25
However, in the case where farmers have Cobb-Douglas preferences, trade unambiguously increases the welfare of farmers. To see this, note that unit price elasticity ensures all risk faced by producers in autarky is aggregate risk (since nominal revenue is invariant to the productivity shock). As a result, the equilibrium autarkic allocation of time to each good is simply its expenditure share. From a simple revealed preference argument, this implies that trade is always (weakly) welfare improving, as producers could have always chosen the autarkic allocation, which with Cobb-Douglas preferences would ensure that no trade occurs. Intuitively, by decoupling the production and consumption decisions, trade converts the aggregate price index risk farmers would face in autarky to idiosyncratic crop specific risk, allowing farmers allocate their crops in such a way so as to reduce their risk exposure.

When goods are substitutes, however, moving from autarky to costly trade can reduce the welfare of farmers. To see this, consider the following two-good two-country example, which is illustrated in Figure 3.

For simplicity, suppose that consumers in both countries have identical preference parameters, are equally risk averse and goods are substitutes ($\sigma > 1$). As depicted in the top panel of Figure 3, we assume that the two countries are symmetric in terms of productivity, with country 1 relatively more productive in good 1 (i.e. has a higher average log yield) and country 2 in good 2. The only asymmetry is that country 1 has more volatile weather, and so the production of the less hardy crop, good 1, in country 1 is risky; all other production is riskless.\(^{25}\)

The middle panel of Figure 3 depicts the equilibrium allocation of time across the two goods. In country 2 in autarky, because production is riskless and goods are substitutes ($\sigma > 1$), most time will be allocated to good 2 as it is more productive. In country 1 in autarky, because producers are sufficiently risk averse and the production of good 1 is risky, they too will allocate more time to good 2, even though they are better at producing good 1. When the two countries open up to trade (which we model as a move from $\varepsilon_{12} = \varepsilon_{21} = 0$ to $\varepsilon_{12} = \varepsilon_{21} = 1$), given its comparative advantage, location 2 will specialize even more in crop 2 and export it. The influx of crop 2 from abroad raises the relative price of crop 1 in location 1. This will cause location 1 to produce more of crop 1 (relative to autarky), although farmers will still allocate a majority of their time to the less risky crop 2.

The bottom panel of Figure 3 depicts the resulting change in welfare for farmers in both countries. In country 2, although opening to trade creates some price volatility, the traditional gains from specialization dominate and welfare increases. In country 1,

\(^{25}\)In particular, we assume $\sigma = 5$, $\rho = 5$ and $\alpha_{ig} = 5$ for $i \in \{1,2\}$ and $g \in \{1,2\}$ on the preference side; and $\mu_{11}^y = \mu_{22}^y = 1$, $\mu_{21}^y = \mu_{12}^y = 0$, $\Sigma_{11}^y = 1$, and $\Sigma_{12}^y = \Sigma_{21}^y = \Sigma_{22}^y = 0$ on the production side.
however, opening to trade increases the volatility of real returns more than average real returns increase, so that farmers in country 1 are actually worse off from trade. Why does this occur? As in a standard trade model, because country 2 specializes relatively more in crop 2 opening up to trade increases the relative price of crop 1. Because farmers in country 1 find crop 1 risky, they allocate a majority of their time to the production of crop 2—despite being much more productive in crop 1—and so the trade-induced price change makes farmers in country 1 worse off.\footnote{We should note that while the fact that trade can make farmers worse off in the presence of uncertainty echoes Newbery and Stiglitz (1984), the mechanism here is slightly different. In Newbery and Stiglitz (1984), a necessary condition for the result is the assumption that there are two types of individuals in a location, with different levels of risk aversion, and each of which only consumed what the other produced. (Assumptions we can dispense with here.) Our result instead relies upon the assumption that traders capture the price arbitrage rents.}

It is important to emphasize that the above analysis has focused on the welfare of farmers and abstracted from the price arbitrage rents enjoyed by traders. Because traders will always be (weakly) better off with trade, the fact that farmers can be made worse off does not imply that trade is welfare reducing as a whole. However, in the example above it is straightforward to show that volatility reduces the arbitrage rents of traders in location 1. Intuitively, because farmers in location 1 did not specialize in their comparative advantage good as much as they would have in the absence of volatility, there was a smaller difference in autarkic prices between the two locations, leading to less of an arbitrage opportunity for traders. Hence, the example shows that volatility can reduce the total gains from trade.

**Insurance can make farmers worse off**

One might think that in the presence of volatility, offering farmers insurance will unambiguously increase their welfare. While this is true when farmers collude to account for general equilibrium effects as in the farmer cooperative extension above,\footnote{This result follows directly by applying the envelope theorem to the time allocation problem of the farmer cooperative.} when farmers are price takers, offering insurance can actually make farmers worse off. Figure 4 provides such an example. The top panel reports the production technologies. As in the previous example, we assume farmers in both locations have identical preferences and that country 1 (2) has an absolute advantage in the production of good 1 (2). Unlike the previous example, we now assume preferences are such that the expenditure share in both countries is heavily tilted toward good 2, so that from the perspective of farmers in country 1, good 1 is a “cash crop” like cotton that has high but variable yields and is not consumed very much locally.

The middle panel of Figure 4 reports the equilibrium time allocation across crops both
with and without (perfect) insurance. In both cases, we assume there is costly trade
(which as above we model with $\varepsilon_{12} = \varepsilon_{21} = 1$). Regardless of the level of insurance,
country 2 almost completely specializes in the production of good 2, as they consume
large quantities of it and they are more productive producing it than good 1. Without
insurance, country 1 produces nearly equal amounts of both goods, as the risk of produc-
ing cash crop 1 roughly offsets its high average yield (and high price). With insurance,
however, farmers in country 1 almost completely specialize in the cash crop, as the return
is high and they are insured from all risk.

The bottom panel of Figure 4 reports the welfare of farmers in both locations, both
with and without insurance. Farmers in country 1 are actually worse off with insurance.
This occurs because price taking farmers do not account for how their allocation decision
will affect the price: as insurance causes (nearly) all farmers in country 1 to move into pro-
duction of the cash crop, the relative price of good 2 rises, reducing their nominal revenue
as they primarily produce crop 1 and making their consumption bundles more expensive
as they primarily consume crop 2. In this example, insurance obviates the welfare loss
from volatility but this benefit is smaller than this reduction in average real returns.

5 Quantifying the welfare effects of volatility and trade

We now bring the model developed above to the data to quantify the welfare effects
of volatility in rural India. We first estimate the preference parameters using household
survey data. We then show that the model yields structural equations that allow us to
easily estimate key model parameters, namely the trade openness of each location and
the sufficient statistic for the trade off between risk and return (a function of risk aversion
and access to insurance). Next, we show that the estimated parameters appear reasonable,
in the sense that they correlate appropriately with observable proxies not used in the esti-
mation. Finally, we use the estimates to quantify the welfare effects of volatility and trade
for India.

5.1 Estimation

In order to quantify the welfare effects of volatility, we need to know the full set of
structural parameters, namely: the mean and variance-covariance matrix for the yields of
all goods produced (net of the costs of production), i.e. $\mu^y$ and $\Sigma^y$, the matrix of shape
parameters governing trade costs, i.e. $\{\varepsilon_{ij}\}_{i \neq j}$, the sufficient statistic $\psi_i$ which captures
the risk aversion / level of insurance of farmers in that location, and the preference pa-
rameters $\{\alpha_{ig}\}$ and $\sigma$. 
Estimating the preference parameters from variation in budget shares and prices

We can recover the preference parameters \( \{ \alpha_{ig} \} \) and elasticity of substitution \( \sigma \) by estimating the CES demand function implied by equation 3:

\[
\ln \left( \frac{C_{ig}}{Y_i} \right) = (1 - \sigma) \ln p_{ig} - (1 - \sigma) \ln P_i + \ln \alpha_g
\]

(28)

where \( P_i = (\sum_g \alpha_g (p_{ig})^{1-\sigma})^{\frac{1}{1-\sigma}} \). We regress log budget shares on the village-level median price-per-calorie using the detailed household-level consumption surveys from the 1987-88 NSS described in Section 2.2. The elasticity is recovered from the coefficient on local prices, the price index term is accounted for by the district fixed effects, and the preference parameters are recovered from the coefficient on the good fixed effects. As local prices may be endogenous to local demand shocks, we instrument for prices with the log median price-per-calorie in neighboring villages (with the identifying assumption being that supply shocks are spatially correlated but demand shocks are not).

Estimating openness to trade from the observed relationship between local prices and yields

From equation (11), the observed local price in any location is a log linear combination of yields across all locations, where the elasticities depend on the distribution of bilateral trade costs. Taking logs of this equation and replacing the state of the world \( s \) with the year \( t \), we obtain:

\[
\ln p_{igt} = - \sum_{j=1}^{N} T_{ij} \ln y_{jgt} + \delta_{it} + \delta_{ig}
\]

(29)

where \( \delta_{it} \equiv \sum_{j=1}^{N} T_{ij} \ln D_{jt} \) is a location-year fixed effect capturing the weighted aggregate destination demand and \( \delta_{ig} \equiv \sum_{j=1}^{N} T_{ij} \ln \frac{\delta_{jt}}{\theta_{ig}} \) is a location-good fixed effect capturing the weighted destination demand relative to supply. While equation (29) follows directly from the structural equation (11), it also has an intuitive interpretation: locations are more open to trade the less responsive their local prices are to local yield shocks and the more responsive they are to yields shocks elsewhere.

Hence, the matrix \( T \) can, in theory, be recovered by projecting observed (log) price on observed (log) yields in every destination conditioning on the appropriate fixed effects. A fully flexible estimation of the \( N \times N \) matrix \( T \) from (29) requires there to be a large number of goods and time periods relative to the number of locations (in particular \( G \times T \geq N + T + G \)), which unfortunately is not the case in our empirical context. Hence,
we make the following parametric assumption:

\[ T_{ij} = \begin{cases} 
\beta + \tilde{v}_{ii} & \text{if } i = j \\
\gamma D_{ij}^{-\phi} + \tilde{v}_{ij} & \text{if } i \neq j
\end{cases} \]  

(30)

where \( D_{ij} \) is the travel time between \( i \) and \( j \) and \( \{\tilde{v}_{ij}\}_j \) are idiosyncratic error terms. This allows us to rewrite equation (29) as:

\[ \ln p_{igt} = -\beta \ln y_{igt} - \gamma \sum_{j \neq i} D_{ij}^{-\phi} \ln y_{jgt} + \delta_{it} + \delta_{ig} + v_{igt}, \]  

(31)

where \( v_{igt} \equiv \sum_{j=1}^{N} \tilde{v}_{ij} \ln y_{jgt} \) is a composite of the idiosyncratic error terms. Given \( D_{ij}^{-\phi} \), the coefficients \( \beta \) and \( \gamma \) can be identified using ordinary least squares as long as yields are uncorrelated with the residual. With estimates of \( \beta \) and \( \gamma \) in hand, and the assumed parametric form from equation (30), we can construct the estimated matrix \( \hat{T} \) and recover the matrix of the distribution of bilateral trade costs through inversion: \( \hat{E} = \hat{T}^{-1} \), where \( \hat{e}_{ij} = -\hat{E}_{ij} \) for \( i \neq j \).

As described in Section 2.2, the VDSA data provide the local price and yield for each year-crop-district triad, and travel times come from the digitizing many years of the Road Map of India. As the parametric form for \( T_{ij} \) is closely related to the parametrization of our market access measure used to generate Stylized Fact 1B, we use the same \( \phi \)s and travel time specifications as used in Section 3.

**Estimating level of insurance and costs of cultivation from observed distribution of yields and allocation decisions**

From Section 4.5, farmers choose a time allocation along the frontier of the (log) mean real returns and the variance of (log) real returns, with the gradient of the frontier at the chosen allocation equal to their level of risk-aversion/access to insurance parameter \( \psi_i \). This implies that any produced good that has higher mean real returns must also contribute a greater amount to the variance of the real returns, as if this were not the case, the farmer should have allocated more time to that good, which would have lowered its mean return. This relationship is summarized in the farmer’s first order conditions from equation (27), which we re-write here:

\[ \mu^{iz}_{S} + \frac{1}{2} \Sigma^{iz}_{S} = \psi_i \sum_{h=1}^{I} \Sigma^{iz}_{gh} \theta_{fih} + \lambda_{fi}. \]  

(32)

Equation (32) forms the basis of our estimation of the level of risk-aversion/access to insurance and the costs of cultivation. Note that if we observed the distribution of real returns and the variance-covariance matrix of real returns, we could directly regress the
former on the latter with a district-decade fixed effect in order to recover $\psi_i$.

However, instead we observe the prices, yields and area allocated to each good in each year and each district from the VDSA data, which has several limitations: first, we have land not time allocations; second, we do not observe the non-agricultural good; third, they are the nominal rather than the real yields; and fourth, they are the yields gross rather than net of costs. To address the first problem, we convert the fraction of land area allocated to a crop to its time allocation by multiplying the land area by the fraction of people employed in agriculture.\(^{28}\) To address the second problem, we set the price of the non-agricultural good as the numeraire, use the observed non-agricultural wage as the measure of the yield, and use the fraction of people not employed in agriculture as the time allocation. To address the third problem, we note that given the distribution of trade costs estimated in the previous subsection, we can use Proposition 1 to transform the mean and variance-covariance matrix of the (observed) nominal gross yields into the mean and covariance of real returns.\(^{29}\) To address the fourth problem, we assume that each good within a district-decade has an unobserved constant multiplicative “iceberg” production cost $\kappa_{igd}$, so that the nominal yield net of costs in any given year is $y_{igd}$. Note that the unobserved costs of cultivation, $\kappa^d_y \equiv \{ \kappa_{igd} \}_g$, do not affect the variance of (log) real returns because they simply shift the mean of the log real returns. As a result, we can re-write equation (32) solely as a function of observables:

$$y_{igd} = \psi_idx_{igd} + \delta_{id} + \delta_{gd} + \nu_{igd}, \quad (33)$$

where $y_{igd}$ is the (log) expected real return of good $g$ in district $i$ in decade $d$, $x_{igd} \equiv \Sigma_{h=1}^{\Sigma_{iz} \theta_{fih}}$ is the marginal contribution to the log variance, $\delta_{id}$ is a district-decade fixed effect which captures the Lagrange multiplier on the first order conditions, $\delta_{gd}$ is a good-decade fixed effect which captures the average difference across goods in their real costs, $\nu_{igd}$ is a residual which captures the deviation from the average costs of good $g$ in decade $d$ in district $i$, and $\psi_id$ is the risk-aversion/insurance parameter for district $i$ in decade $d$.

Under the assumption that the production costs are constant within district-decade (and hence mechanically uncorrelated with the covariance of the log real returns), $\psi_id$ can be estimated using equation (33) using ordinary least squares. Furthermore, using

\(^{28}\)This procedure is valid under the assumption that the time of cultivation is constant across crops. Because it is certainly true that crops differ in the intensity of their labor inputs, we allow for the cost of cultivation to differ across crops which will capture these differences.

\(^{29}\)Some aggregation is necessary in order for us to estimate the variance-covariance matrix of yields and prices. We aggregate across district-decade, implicitly assuming that time allocation are constant within decade. In what follows, we therefore construct the time allocation within district-decade by averaging across years.
Proposition 1, it can be shown that the district-decade specific production costs can be recovered from the estimated good-decade fixed effect as follows:\(^{30}\)

\[ \kappa_{yd} = (I - T)^{-1} (\delta_{gd} + \nu_{igd}) \cdot \]

Note that given these estimated production costs (along with the other estimated structural parameters), the farmer’s first order conditions will hold with equality at their observed time allocation, i.e. farmers in all districts and all decades will have chosen allocations at the optimal point along the mean-variance frontier.

Equation (33) follows directly from the structural equation (32) but has a straightforward interpretation: at the optimal allocation crops that have higher mean returns must also have higher (marginal contributions to overall) volatility. The more (less) risk the farmer is willing to accept in order to increase her mean returns, the less (more) risk averse she is (and/or the better (worse) access to insurance she has).

5.2 Estimation results

Table 4 presents the estimated demand parameters using the methodology described above. The implied elasticity of substitution is 2.4 using our preferred IV specification.

Table 5 reports the results of regression (31). As can be seen, prices are lower when both own yields and the distance-weighted sum of other districts’ yields are higher. The implied \(\beta\) and \(\gamma\) are positive and statistically significant across all specifications, regardless of our choice of \(\phi\) (either \(\phi = 1\) or \(\phi = 1.5\)), our estimate of the off-highway speed of travel (1/3 or 1/4 of that on the highway), and whether or not we include districts for which the yield has been interpolated. In our preferred specification (column 1), the estimates imply that the average Pareto shape parameter in 1970 was 0.037, rising to 0.050 by 2000, indicating high trade costs across locations.\(^{31}\)

Table 6 reports the results from the estimation of the risk-aversion/insurance parameters \(\{\psi_{id}\}\). Column 1 reports that the average \(\psi_{id}\) across all districts and decades is approximately 1.4. Recalling that log-utility has a coefficient of relative risk aversion of one, this indicates that farmers on average are quite risk averse and have little access to ex-post insurance. Columns 2 and 3, however, show that the estimated risk aversion is negatively

\(^{30}\)Because the fixed effect \(\delta_{gd}\) are only identified up-to-scale, identifying the level of production costs requires a normalization. We assume that there are no production costs associated with the production of the non-agricultural good. Because the overall level of costs does not affect the allocation decision of farmers, this assumption only matters when comparing welfare across decades, where it imposes that the “disutility” of non-agricultural work is constant across time.

\(^{31}\)While the estimated shape parameters are quite low, recall that we assume the iceberg trade costs are drawn independently across location. Since there are more than 300 districts, the low values of the shape parameters are necessary in order to ensure that the probability of sourcing or selling locally remains high.
and statistically significantly correlated with access to formal credit (measured by number of banks per capita or log number of banks, respectively), even after controlling for both district and decade fixed effects. This implies that districts which had disproportionately greater increases in access to credit over time were also those where farmers appeared to be more willing to move toward riskier allocations in exchange for higher mean real returns. Since the number of banks did not enter our structural estimation, we view this as evidence that our structural estimates of $\psi_i$ are indeed capturing variation in the ability of farmers to insure themselves.

One problem that arises in estimating the risk-aversion/insurance parameter $\psi_{id}$ separately for all 1,200 districts-decade pairs is that, due to estimation error, there will be instances where the estimate of $\psi_{id}$ is negative. Since we have a strong prior that farmers are not risk loving, we also pursue a maximum a posteriori (MAP) Bayesian estimation strategy, where we assume that each $\psi_{id}$ is drawn from a log-normal distribution (and hence is strictly positive). As we show in Appendix A.3, the MAP estimator bears a close resemblance to the ordinary least squares estimator:

$$\hat{\psi}_{MAP} = \frac{\hat{\psi}_{OLS} + \left(\hat{\psi}_{OLS}^2 + 4se(\hat{\psi}_{OLS})^2\right)^{1/2}}{2}.$$  

Intuitively, in the limit where the ordinary least squares estimate of $\psi$ has a standard error of zero, the MAP and OLS estimates coincide if the OLS estimator is positive. If the OLS estimator is negative, then the smaller the standard error, the closer to zero the MAP estimator is. Conversely, the greater the OLS standard error, the more the MAP estimator adjusts the OLS estimator upwards. Column 4 of Table 6 shows the $\hat{\psi}_{MAP}$ estimates. The average MAP estimator is 1.66, higher than the OLS estimator but not dramatically so. Columns 5 and 6 show that the correlation with the observed access to banks remain very similar to the OLS estimates.

5.3 Trade, volatility, insurance and welfare

We now use our structural estimates to quantify the welfare effects of trade and volatility. To isolate the gains from trade, for every district, we hold all structural parameters except openness (i.e. the distribution of yields net of costs and the risk-aversion/insurance parameter) constant at the estimated level for the 1970s and then re-calculate the equilibrium crop choice and distribution of real returns and the resulting welfare for the estimated distribution of bilateral trade costs in the 1980s, 1990s, and 2000s. This procedure isolates the gains coming about purely from changes in trade costs, i.e. the gains from trade.
Figure 5 shows the results from this counterfactual. The top left panel shows that as trade costs fall due to the expansion of the Indian highway system, the mean real returns to farmers increase. However, the top right panel shows that this increase in mean real returns is accompanied by an increase in the variance of real returns as well. The bottom left panel shows that the overall effect on welfare is positive; comparing the magnitude of the welfare effects to the first moment effects, we see that the increase in volatility reduced the first moment welfare gains by roughly one fifth. Hence, while reductions in trade costs due to the expansion of the highway network substantially reduced farmer welfare by increasing the volatility farmers faced, this welfare loss was dwarfed by the first moment gains from trade.

How do the gains from trade interact with insurance? To answer this question, we proceed as above but now also allow the level of insurance to change over time by feeding in our time-varying estimates of $\psi_{id}$, the risk aversion/access to insurance parameter. The navy blue bars in Figure 6 presents these results (where the red bars report the welfare changes from just allowing the trade costs to change, i.e. they replicate the results in Figure 5). As is evident, the improvement in access to insurance over the forty years of our sample increases the mean real returns (top left panel), but at the cost of greater volatility (top right panel). These changes in access to insurance magnified the total gains from trade in the 1980s and the 1990s, but attenuated the gains from trade in the 2000s.

Why are the gains from trade in the 2000s smaller with insurance? Figure 7 shows that when farmers are offered better insurance, they reallocate their production toward higher risk, higher return “cash crops” like cotton and away from staple crops like rice and wheat. Because very little cotton is consumed relative to rice and wheat, this reallocation toward cash crops increases the cost of the farmers’ consumption bundle, reducing the mean real returns. (Recall from above, this loss from insurance can only occur when farmers take prices as given rather than accounting for how their allocation affects prices through general equilibrium effects).

An extreme counterfactual sheds more light on the interactions between trade and insurance. We consider the welfare gains if, simultaneously to the estimated reductions in trade costs, farmers had been offered perfect insurance. The effect on welfare and crop choices is shown in the green bars of Figures 6 and 7, respectively. Offering farmers perfect insurance causes substantial reallocation toward cash crops and away from staple crops, which actually results in a net decline in the mean real returns farmers earn as the cost of consumption dramatically increases. Furthermore, given the riskiness of the cash crops, the variance of real returns increases substantially. However, since the welfare of perfectly insured farmers is not affected by the increase in variance, this direct gain from
insurance more than offsets the fall in real returns and the gains from trade are amplified by perfect insurance. As the structural estimates and counterfactuals highlight, the effect of insurance on farmers’ allocations and the resulting general equilibrium price effects can have dramatically alter the welfare gains from insurance provision during times of increasing trade openness.

6 Conclusion

The goal of this paper has been to examine the relationship between trade and volatility. To do so, we first document that reductions in trade costs owing to the expansion of the Indian highway network have reduced in magnitude the negative relationship between local prices and local yields, which has caused farmers to reallocate their land toward crops with higher mean yields and lower yield volatility. We then present a trade model whereby risk averse producers choose their optimal allocation of resources across goods and the general equilibrium distribution of real returns is determined by the distribution of bilateral trade costs and yields. The model yields tractable equations governing equilibrium prices and farmers’ resource allocations and straightforward explanations for the patterns documented in the data.

Given the structure of the model, we identify both the bilateral trade costs—using the relationship between local prices and yield shocks in all locations—and farmers’ risk preferences—using the slope of the mean-variance frontier at the observed crop choices. Using these estimates, we show that while increased trade openness did reduce farmer welfare by increasing volatility, these welfare losses were relatively small compared to the first moment gains from trade. Increased insurance options would be expected to mitigate the negative impacts of rising volatility. However, we find that that any benefits from reduced risk can be fully offset by increases in the cost of the consumption bundle due to reallocations of resources toward the production of riskier cash crops.

This paper contributes both to a distinguished theoretical literature and a emerging empirical literature examining the second moment effects of trade and the role of insurance. However, several important questions remain: What is the optimal level of insurance to offer to farmers? What would the effect be of offering insurance across locations? What are the effects of volatility on traders? Addressing these questions are fruitful directions for future research.
References


Journal of international Economics, 82(1), 26–34.


Table 1: Volatility and Market Access

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<th>Dependent Variable:</th>
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<td>Market Access</td>
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<tr>
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<td>(0.006) (0.007) (0.002) (0.004) (0.889) (1.353) (0.051) (0.078)</td>
</tr>
<tr>
<td>Market Access (phi=1)</td>
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<td>(0.002) (0.005) (0.001) (0.002) (0.377) (1.136) (0.018) (0.047)</td>
</tr>
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<td>Market Access (pop. weights)</td>
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<td>(0.032) (0.133) (0.014) (0.045) (5.637) (12.831) (0.288) (0.805)</td>
</tr>
<tr>
<td>Market Access (alt. speed)</td>
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<td>Observations</td>
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Notes: Each cell represents one regression. Components of volatility (coefficients of variation of revenues, prices and yields and the correlation between prices and yields) regressed on market access multiplied by 100,000. Each observation is a district-decade pair. Ordinary least squares. Observations are weighted by the number of non-missing observations within a district-decade. Standard errors clustered at the district-decade level are reported in parentheses. Stars indicate statistical significance: * p<.10 ** p<.05 *** p<.01.
Table 2: Price Production Elasticities and Roads

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<td>Observations</td>
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Notes: Estimates of the elasticity of local prices to production regressed on market access multiplied by 100,000. Each observation is a crop-district-decade. Observations are weighted by the inverse of the variance of the elasticity estimate. Both estimates and weights winsorized at the 1 percent level. Elasticity is the coefficient of a regression of log prices on log production for a particular crop-district-decade. All columns instrument production with local rainfall shocks bar column 3 which shows the OLS. Standard errors clustered at the district-decade level are reported in parentheses. Stars indicate statistical significance: * p<.10 ** p<.05 *** p<.01.
### Table 3: Crop Choice and Openness

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<td>0.002**</td>
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**Crop-decade FE**: Yes, Yes, Yes, Yes, Yes, Yes, Yes, Yes, Yes  
**District-decade FE**: Yes, Yes, Yes, Yes, Yes, Yes, Yes, Yes, Yes  
**Crop-district FE**: Yes, Yes, Yes, Yes, Yes, Yes, Yes, Yes, Yes  
**R-squared**: 0.975, 0.975, 0.975, 0.975, 0.975, 0.975, 0.975, 0.975  
**Observations**: 14030, 14030, 13999, 14030, 13999, 14030, 13999, 14030, 13999

**Notes**: Ordinary least squares. Crop choice regressed on the log mean and variance of yields, and the log mean and variance of yields interacted with market access multiplied by 100,000 and or banks per capita multiplied by 1000. Each observation is a crop-district-decade. Observations are weighted by the number of years observed within decade. Standard errors clustered at the district-decade level are reported in parentheses. Stars indicate statistical significance: * p<.10 ** p<.05 *** p<.01.
Table 4: Preference Parameters

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<td>IV</td>
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<td>Barley $\alpha$</td>
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Notes: Estimates of the elasticity of local budget shares to village-level median prices. Each observation is a household-good pair from the 1987 NSS household surveys. Observations are weighted by NSS survey weights. IV estimates instrument log median village prices with log median village prices in neighboring village. Coefficients on prices transformed by $1 - x$, good fixed effects transformed by $e^x$. Standard errors clustered at the village level are reported in parentheses. Stars indicate statistical significance: * p<.10 ** p<.05 *** p<.01.
<table>
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<th>(5)</th>
<th>(6)</th>
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<td>-0.037***</td>
<td>-0.039***</td>
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| District-year FE     | Yes | Yes | Yes | Yes | Yes | Yes |
| Crop-district-decade FE | Yes | Yes | Yes | Yes | Yes | Yes |
| R-squared            | 0.930 | 0.930 | 0.930 | 0.929 | 0.929 | 0.929 |
| Observations         | 84158 | 84158 | 84158 | 88417 | 88417 | 88417 |

Notes: Ordinary least squares. Estimates of local prices regressed on own log yields and travel time weighted average of other districts’ yields. Each observation is a crop-district-year. Standard errors reported in parentheses. Stars indicate statistical significance: * p<.10 ** p<.05 *** p<.01.
Table 6: Estimated Risk Aversion and Insurance

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<th>MAP</th>
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<td>(0.409)</td>
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<td>(0.132)</td>
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</table>

Notes: Ordinary least squares. Each observation is a district-decade. The dependent variable is the district-decade specific estimated coefficient of a regression of the mean real returns of a crop on its contribution to the log variance of total real returns, where the regression includes district-decade and crop-decade fixed effects. Observations are weighted by the inverse of the square of the standard error of the estimated coefficient from that regression, where that standard error is clustered by district decade and winsorized at the 1%/99% level. Robust standard errors are reported in parentheses. Stars indicate statistical significance: * p<.10 ** p<.05 *** p<.01.
Notes: This figure shows the expansion of the Indian highway network over time. The networks are constructed by geocoding scanned road atlases for each of the above years and using image processing to identify the pixels associated with highways. Bilateral distances between all districts are then calculated by applying the “Fast Marching Method algorithm (see Sethian (1999)) to the resulting speed image.
Figure 2: Decomposition of Revenue Volatility over Time

Notes: This figure shows how and why the volatility of agricultural revenue has changed over time. The blue bar reports the volatility in total agricultural revenue using observed crop-year-district prices, yields, and share of land. The red, green, and orange bars report the fraction of this volatility due to price volatility, yield volatility, and the covariance between prices and yields using the decomposition discussed in the text. The gray bar captures the residual portion of the volatility which arises due to the second order approximation used in the decomposition as well as any within decade-district changes in land allocated to different crops. Volatility is measured as the variation in log revenue. Each of the values reported are the median value across districts within a decade.
Figure 3: Example of farmers being made worse off from trade

Notes: This figure shows an example where opening up to trade reduces the welfare of farmers in a location. Please see Section 4.6 for a complete description of the effects.
Figure 4: Example of farmers being made worse off from insurance

Notes: This figure shows an example where offering farmers (perfect) insurance can reduce their welfare. Please see Section 4.6 for a complete description of the effects.
Figure 5: Structural Estimates: Gains from trade

Notes: This figure shows the effect of trade on farmer’s welfare over time. For each decade, we calculate the optimal counterfactual crop choice given 1970s production technologies and level of insurance with the contemporary bilateral trade costs. All values are for the median district within a decade and report the difference from the level in the 1970s. The top left panel reports the average real returns across decade; the top right panel reports the variance of the log real returns across decade; the bottom left panel reports the welfare across decade. Welfare is measured as the change in certainty equivalent income (1960s rupees per hour).
Figure 6: Structural Estimates: Insurance and the gains from trade

Notes: This figure shows how access to insurance affects the gains from trade. The red bar (which is replicated from Figure (5)) reports the change in welfare effect of changing trade openness, holding all other structural parameters constant. The blue bar reports the welfare effect of changing both trade openness and access to insurance, holding production technologies constant. The green bar reports the what the welfare effect would have been had farmers had access to perfect insurance. All values are for the median district within a decade and report the difference from the level in the 1970s. The top left panel reports the average real returns across decade; the top right panel reports the variance of the log real returns across decade; the bottom left panel reports the welfare across decade. Welfare is measured as the change in certainty equivalent income (1960s rupees per hour).
Notes: This figure shows how access to insurance and trade affect crop choice. The figure illustrates the change in the allocation of land for three important crops: cotton (a cash crop for which very little is consumed locally) and rice and wheat, which are both staples. The bars report the average change from the 1970s in the resources allocated to each of the crops under three scenarios: (1) (red bar) the contemporary openness to trade, holding all other structural parameters fixed at 1970s levels; (2) (blue bar) the contemporary openness to trade and level of insurance, holding production technologies fixed at 1970s levels; and (3) (green bar), the contemporary openness to trade along with the counterfactual perfect insurance, holding production technologies fixed at 1970s levels.
A Appendix

A.1 Proof of Proposition 1

Proposition. [restated] Define $z_i(s)$ as the $G \times 1$ vector of $z_{ig}(s)$. Then the joint distribution of real returns across goods is log-normal, i.e.

$$\ln z_i \sim N\left(\mu_i^z, \Sigma^z\right),$$

where:

$$\mu_i^z \equiv \left(\mu^{iy} - \sum_{j=1}^{N} T_{ij} \left(\mu^{iy} - \tilde{\alpha}_j^i \mu^{jy}\right)\right) + c^i$$

$$\Sigma^z \equiv (I - T_{ii} (1_G - (1_G \alpha_i^i))) \Sigma^{iy} (I - T_{ii} (1_G - (1_G \alpha_i^i)))' + \sum_{j \neq i} (T_{ij})^2 \left(1_G - \left(1_G \alpha_j^i\right)\right) \Sigma^{jy} (1_G - \left(1_G \alpha_j^i\right))'$$

$$c^i \equiv \left\{\sum_{j=1}^{N} T_{ij} \ln \left(\frac{\alpha_{jg}}{\theta_{jg}}\right)\right\}_g - \sum_{j=1}^{N} T_{ij} \sum_{h=1}^{G} \alpha_{jh} \ln \left(\frac{\alpha_{jh}}{\theta_j}\right) + (\sigma - 1) \sum_{j=1}^{N} \sum_{h=1}^{G} T_{ij}^2 \sum_{h=1}^{G} \alpha_{jh} \left(\sum_{h=1}^{G} \frac{\alpha_{jh}}{\theta_j} - \sum_{l=1}^{G} \Sigma_{hl} \alpha_{jl}\right)$$

Furthermore, to a second order approximation, total real income $Z_{fi}(s) \equiv \sum_{g=1}^{G} \theta_{fig} z_{ig}(s)$ is also log normally distributed:

$$\ln Z_{fi}(s) \sim N\left(\mu_i^Z, \sigma_i^2\right),$$

where:

$$\mu_i^Z \equiv \tilde{\theta}_{fi} \left(\mu_i^z + \frac{1}{2} \text{diag} \left(\Sigma^z\right)\right) - \frac{1}{2} \tilde{\theta}_{fi} \Sigma^z \tilde{\theta}_{fi}$$

$$\sigma_i^2 \equiv \tilde{\theta}_{fi} \Sigma^z \tilde{\theta}_{fi},$$

and $\tilde{\theta}_{fi}$ is the $G \times 1$ vector whose $g^{th}$ element is $\theta_{fig}$.

Proof. Define $v_i(s)$ as the $G \times 1$ vector with $g^{th}$ element $\left(\prod_j \left(\frac{\alpha_{jg}}{\theta_{jg}}\right)^{T_{ij}}\right)^{1-\sigma}$.

Taking logs yields:

$$\ln v_{ig}(s) = (\sigma - 1) \sum_{j=1}^{N} T_{ij} \ln y_{jg}(s) + (1 - \sigma) \sum_{j=1}^{N} T_{ij} \ln \left(\frac{\theta_{jg}}{\alpha_{jg}}\right)$$

so that given Assumption 1, $\ln v_{i} \sim N\left(\mu^{iv}, \Sigma^{iv}\right)$, where $\mu^{iv} = (\sigma - 1) \sum_{j=1}^{N} T_{ij} \mu^{jy} + (\sigma - 1) \sum_{j=1}^{N} T_{ij} \ln \left(\frac{\theta_{jg}}{\alpha_{jg}}\right)$ and $\Sigma^{iv} = (\sigma - 1)^2 \sum_{j=1}^{N} T_{ij}^2 \Sigma^{jy}$. 

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To a second order approximation, we have:

$$\ln V(s) \equiv \ln \sum_{s} G \alpha_{s} v_{is} (s) \approx \sum_{s} G \alpha_{s} \ln v_{is} (s) + \frac{1}{2} \sum_{s} G \alpha_{s} \Sigma_{ss}^{iv} - \frac{1}{2} \sum_{s} G \alpha_{s} \Sigma_{gh}^{iv},$$

which implies that $V(s)$ is approximately log normally distributed:

$$\ln V(s) \sim N\left(\mu_{IV}, \sigma_{IV}^{2}\right),$$

where $\mu_{IV} \equiv \sum_{s} G \alpha_{s} \mu_{is} + \frac{1}{2} \sum_{s} G \alpha_{is} \Sigma_{ss}^{iv} - \frac{1}{2} \sum_{s} G \alpha_{is} \Sigma_{gh}^{iv}$ and $\sigma_{IV}^{2} \equiv \sum_{s} G \alpha_{is} \Sigma_{gh}^{iv}$.

With this approximation, we can write the log real returns as follows:

$$\ln z_{ig} (s) \approx \ln y_{ig} (s) - \sum_{j=1}^{N} T_{ij} \left(\ln y_{ij} (s) - \left(\sum_{h=1}^{G} \alpha_{h} \ln y_{jh} (s)\right)\right) + \sum_{j=1}^{N} T_{ij} \left(\ln \left(\frac{\alpha_{s}}{\bar{\theta}_{ij}}\right) - \sum_{h=1}^{G} \alpha_{h} \ln \left(\frac{\alpha_{h}}{\bar{\theta}_{ij}}\right)\right).$$

In vector notation, we can write:

$$\ln z_{i} (s) \approx \ln y_{i} (s) - \sum_{j=1}^{N} T_{ij} (1_{G} - (1_{G} \alpha')) \ln y_{j} (s) + \bar{c}_{i}, \quad (34)$$

where $\bar{c} \equiv \left\{\sum_{j=1}^{N} T_{ij} \ln \left(\frac{\alpha_{s}}{\bar{\theta}_{ij}}\right)\right\} - \sum_{j=1}^{N} \sum_{h=1}^{G} \alpha_{h} \ln \left(\frac{\alpha_{h}}{\bar{\theta}_{ij}}\right) + \frac{1}{\sigma_{-1}} \frac{1}{2} \sum_{h=1}^{G} \alpha_{h} \Sigma_{hh}^{iv} - \frac{1}{\sigma_{-1}} \frac{1}{2} \sum_{h,l}^{G} \alpha_{h} \alpha_{l} \Sigma_{hl}^{iv}$.

Applying assumption 1 to equation (34) using the familiar formula for the affine transformation of a multivariate normal distribution yields the first part of the proposition. The second part of the proposition applies the same second order Taylor approximation and then again applying the formula for an affine transformation of a multivariate normal distribution:

$$\ln \left(\sum_{s=1}^{G} \theta_{fis} z_{is} (s)\right) \approx \sum_{s=1}^{G} \theta_{fis} \ln z_{is} (s) + \frac{1}{2} \sum_{s=1}^{G} \theta_{fis} \Sigma_{ss}^{iz} - \frac{1}{2} \sum_{s=1}^{G} \sum_{l=1}^{G} \Sigma_{sl}^{iz} \theta_{fis} \theta_{fis}. \quad \square$$

### A.2 A microfoundation for insurance

In this subsection, we provide a microfoundation for the assumption that in the presence of (costly) insurance, equilibrium real income after insurance is equal to a Cobb-Douglas combination of equilibrium real income prior to insurance and expected income. To save on notation, in what follows, we will denote states of the world with subscripts and the probability (density) of state of the world $s$ with $\pi_{s}$. Denote the real income realization prior to insurance as $I_{s}$ and denote the real income post insurance as $C_{s}$.

The goal is to show that:

$$C_{s} = \kappa I_{s}^{\chi} E (I_{s})^{1-\chi}, \quad (35)$$

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where $\chi \in [0, 1]$ and $\kappa \equiv \frac{E[I_s]}{E[I_i]}$ is a scalar necessary to ensure that the mean income remains constant before and after insurance.

To micro-found equation (35), we proceed as follows. As in the main text, farmers are assume to be risk averse with constant relative risk aversion, but now we allow them the ability to purchase insurance. A farmer can purchase insurance which pays out one unit of income in state of the world $s$ for price $p_s$. Hence, consumption in state of the world $s$ will be the sum of the realized income in that state and the insurance payout less the money spent on insurance: $C_s = I_s + q_s - \sum_t p_t q_t$. A farmer’s expected utility function is:

$$E[U] = \sum_s \pi_s \left( I_s + q_s - \sum_t p_t q_t \right)^{1-\rho},$$

where as in the main text $\rho \geq 0$ is the level of risk aversion of the farmer.

Farmers purchase their insurance from a large number of “money-lenders” (or, equivalently, banks). Money-lenders have the same income realizations as farmers, but are distinct from farmers in that they are less risk averse. For simplicity, we assume the money-lenders also have constant relative risk aversion preferences with risk aversion parameter $\lambda \leq \rho$. Because lenders are also risk averse, farmers will not be able to perfectly insure themselves. Money lenders compete with each other to lend money, and hence the price of purchasing insurance in a particular state of the world is determined by the marginal cost of lending money.

We first calculate the price of a unit of insurance in state of the world $s$. Since the price of insurance is determined in perfect competition, it must be the case that each money lender is just indifferent between offering insurance and not:

$$\sum_t \pi_t \frac{1}{1-\lambda} (I_t + \epsilon p_s)^{1-\lambda} + \pi_s \frac{1}{1-\lambda} (I_t + \epsilon p_s - \epsilon)^{1-\lambda} = \sum_t \pi_t \frac{1}{1-\lambda} I_t^{1-\lambda},$$

where the left hand side is the expected utility of a money-lender offering an small amount $\epsilon$ of insurance (which pays $\epsilon p_s$ with certainty but costs $\epsilon$ in state of the world $s$) and the left hand side is expected utility of not offering the insurance. Taking the limit as $\epsilon$ approaches zero yields that the price ensures that the marginal utility benefit of receiving $p_s \epsilon$ in all other states of the world is equal to the marginal utility cost of paying $\epsilon (1 - p_s)$ in state of the world $s$.

$$p_s \epsilon \sum_{t \neq s} \pi_t I_t^{1-\lambda} = \epsilon (1 - p_s) \pi_s I_s^{1-\lambda} \iff p_s = \frac{\pi_s I_s^{1-\lambda}}{\sum_{t} \pi_t I_t^{1-\lambda}}.$$
Equation (36) is intuitive: it says that the price of insuring states of the world with low aggregate income shocks is high.

Now consider the farmer’s choice of the optimal level of insurance. Farmers will choose the quantity of insurance to purchase in each period in order to maximize their expected utility:

$$\max_{\{q_s\}} \sum_s \pi_s \frac{1}{1-\rho} \left( I_s + q_s - \sum_t p_t q_t \right)^{1-\rho}$$

which yields the following FOC with respect to $q_s$:

$$\pi_s \left( I_s + q_s - \sum_t p_t q_t \right)^{-\rho} = p_s \sum_t \pi_t \left( I_t + q_t - \sum_t p_t q_t \right)^{-\rho} \iff \frac{\pi_s C_s^{-\rho}}{\sum_t \pi_t C_t^{-\rho}} = p_s.$$  \hfill (37)

Substituting the equilibrium price from equation (36) into equation (37) and noting that $E[C^{-\rho}] = \sum_t \pi_t C_t^{-\rho}$ and $E[I^{-\lambda}] = \sum_t \pi_t I_t^{-\lambda}$ yields:

$$\frac{C_s^{-\rho}}{E[C^{-\rho}]} = \frac{I_s^{-\lambda}}{E[I^{-\lambda}]}.$$  \hfill (38)

As in the paper, suppose that $\ln I \sim N(\mu_I, \sigma_I^2)$. Then we have:

$$\ln \left( \frac{I_s^{-\lambda}}{E[I^{-\lambda}]} \right) \sim N \left( \frac{-1}{2} \lambda^2 \sigma_I^2, \lambda^2 \sigma_I^2 \right),$$

so that it also is the case that ex-post insurance is log normally distributed (with an arbitrary mean of log returns $\mu_C$):

$$\ln \left( \frac{C^{-\rho}}{E[C^{-\rho}]} \right) \sim N \left( \frac{-1}{2} \lambda^2 \sigma_I^2, \lambda^2 \sigma_I^2 \right) \iff -\rho \ln C \sim N \left( \frac{1}{2} \lambda^2 \sigma_I^2 + \ln E[C^{-\rho}], \lambda^2 \sigma_I^2 \right) \iff \ln C \sim N \left( \frac{1}{2} \lambda^2 \sigma_I^2 - \frac{1}{\rho} \ln E[C^{-\rho}], \frac{\lambda^2}{\rho^2} \sigma_I^2 \right) \iff \ln C \sim N \left( \frac{1}{2} \lambda^2 \sigma_I^2 - \frac{1}{\rho} \left( -\rho \mu_C + \frac{1}{2} \rho^2 \sigma_C^2 \right), \frac{\lambda^2}{\rho^2} \sigma_I^2 \right) \iff \ln C \sim N \left( \mu_C, \frac{\lambda^2}{\rho^2} \sigma_I^2 \right),$$

where $\mu_C$ is an arbitrary mean of log returns. The arbitrary mean arises because the first
order conditions (37) are homogeneous of degree zero in consumption, i.e. the first order conditions do not pin down the scale of ex-post real income. To ensure that access to insurance only affects the second moment of returns, we assume that the average income after insurance is equal to average income before insurance, i.e:

\[ E[C] = E[I] \iff \exp\left\{\mu_C + \frac{1}{2} \lambda^2 \sigma_I^2\right\} = \exp\left\{\mu_I + \frac{1}{2} \sigma_I^2\right\} \iff \mu_C = \mu_I + \frac{1}{2} \sigma_I^2 \left(1 - \left(\frac{\lambda}{\rho}\right)^2\right). \]

As a result, we can re-write equation (38) as:

\[
C_s = I_s^{\lambda} E[C^{-\rho}]^{-\frac{1}{\rho}} E\left[I^{1-\lambda}\right]^{\frac{1}{\rho}} \iff \\
C_s = I_s^{\lambda} \exp\left\{-\frac{1}{\rho} \left(-\rho \mu_C + \frac{1}{2} \lambda^2 \sigma_I^2\right) + \frac{1}{\rho} \left(-\lambda \mu_I + \frac{1}{2} \lambda^2 \sigma_I^2\right)\right\} \iff \\
C_s = I_s^{\lambda} \exp\left\{\mu_C - \frac{\lambda}{\rho} \mu_I\right\} \iff \\
C_s = I_s^{\lambda} \exp\left\{\left(1 - \frac{\lambda}{\rho}\right) \mu_I + \frac{1}{2} \sigma_I^2 \left(1 - \left(\frac{\lambda}{\rho}\right)^2\right)\right\} \iff \\
C_s = I_s^{\lambda} \exp\left\{\mu_I + \frac{1}{2} \sigma_I^2\right\} \exp\left\{\frac{\lambda}{\rho} \mu_I + \frac{1}{2} \sigma_I^2 \left(\frac{\lambda}{\rho}\right)^2\right\} \iff \\
C_s = \frac{I_s^{\lambda}}{E[I]} \iff \\
C_s = \kappa I_s^{\lambda} E(I_s)^{1-\chi},
\]

where \(\chi \equiv \frac{\lambda}{\rho} \in [0, 1]\) and \(\kappa \equiv \frac{E[I_s]}{E[I]}\) as claimed.

A.3 Maximum a posteriori estimation where the coefficient is drawn from a log-normal distribution

Assume that we are trying to estimate:

\[ y_i = \alpha + x_i \beta + \epsilon_i \]
where \( \epsilon_i \sim N(0, \sigma^2) \) and \( \ln \beta \sim N(\mu_\beta, \sigma^2_\beta) \), where all parameters are unknown. The likelihood function is then:

\[
L(\beta) = \frac{1}{\beta \sigma_\beta \sqrt{2\pi}} \exp \left( -\frac{(\ln \beta - \mu_\beta)^2}{2 \sigma^2_\beta} \right) \prod_{i=1}^N \frac{1}{\sigma \sqrt{2\pi}} \exp \left( -\frac{(y_i - \alpha - x_i \beta)^2}{2 \sigma^2} \right)
\]

By taking logs and ignoring the constants which do not affect maximization, we have:

\[
\ln L(\beta) = -\ln \beta - \frac{(\ln \beta - \mu_\beta)^2}{2 \sigma^2_\beta} - \sum_{i=1}^N \frac{(y_i - \alpha - x_i \beta)^2}{2 \sigma^2}.
\]

The MAP estimator of \( \beta \) is defined as the parameter estimator that maximizes the log likelihood function:

\[
\hat{\beta}_{MAP} \equiv \arg \max_{\beta \in \mathbb{R}} \left( \max_{\mu_\beta, \sigma_\beta, \sigma, \alpha} \left( -\ln \beta - \frac{(\ln \beta - \mu_\beta)^2}{2 \sigma^2_\beta} - \sum_{i=1}^N \frac{(y_i - \alpha - x_i \beta)^2}{2 \sigma^2} \right) \right)
\]

We first solve the inner maximization problem. The first order conditions with respect to \( \mu_\beta \) is clearly set \( \mu_\beta = \ln \beta \) (so don’t place any weight on deviations from the mean), so that we can write:

\[
\hat{\beta}_{MAP} = \arg \max_{\beta \in \mathbb{R}} \left( \max_{\sigma, \alpha} \left( -\ln \beta - \sum_{i=1}^N \frac{(y_i - \alpha - x_i \beta)^2}{2 \sigma^2} \right) \right).
\]

The first order conditions with respect to \( \alpha \) are:

\[
\hat{\alpha} = \bar{y}_n - \hat{\beta} \bar{x}_n
\]

so that we can write:

\[
\hat{\beta}_{MAP} = \arg \max_{\beta \in \mathbb{R}} \left( \max_{\sigma} \left( -\ln \beta - \sum_{i=1}^N \frac{(y_i - \bar{y}_n - (x_i - \bar{x}_n) \beta)^2}{2 \sigma^2} \right) \right).
\]

Finally, we can take the first order conditions with respect to \( \beta \), which yield:

\[
- \sum_{i=1}^N \frac{((y_i - \bar{y}_n) - (x_i - \bar{x}_n) \hat{\beta}_{MAP}) (x_i - \bar{x}_n)}{\sigma^2} - \frac{1}{\hat{\beta}^2_{MAP}} = 0 \iff \hat{\beta}^2_{MAP} - \hat{\beta}_{OLS} \hat{\beta}_{MAP} - \frac{\hat{\psi}^0}{N} = 0,
\]

where \( \hat{\psi}^0 \equiv \sigma^2 \left( \frac{1}{N} \sum_{i=1}^N (x_i - \bar{x}_n)^2 \right)^{-1} \) is the (homoskedastic) covariance matrix. Recall that the standard error of \( \hat{\beta}_{OLS} \) is \( \left( \frac{1}{N} \hat{\psi}^0 \right)^{\frac{1}{2}} \) so that \( \hat{\beta}_{MAP} \) is the root of the following polynomial:

\[
0 = \hat{\beta}^2_{MAP} - \hat{\beta}_{OLS} \hat{\beta}_{MAP} - se (\hat{\beta}_{OLS})^2
\]
Then applying the quadratic formula we have that the MAP estimate of $\beta$ is:

$$
\hat{\beta}_{MAP} = \hat{\beta}_{OLS} + \left( \hat{\beta}^2_{OLS} + 4se(\hat{\beta}_{OLS})^2 \right)^{\frac{1}{2}}.
$$

**Additional Tables and Figures**

Figure 8: Agricultural revenue over time

**Notes:** This left panel shows the average revenue per hectare for the median district by decade. The right panel shows the median coefficient of variation of average revenue per hectare across years for the median district by decade.
Notes: This figure shows how and why the average of (log) agricultural revenue has changed over time. The blue bar reports changes relative to 1970 in the total average agricultural revenue using observed crop-year-district prices, yields, and share of land. The red and green bars report the fraction of this change due to price changes and yield changes using the decomposition discussed in the text. Each of the values reported are the median value across districts within a decade.
Figure 10: Mean of yields: Examples

Notes: This figure shows the mean of (log) yields across crops for two example districts – Chittagargh, Rajasthan (top row) and Madurai, Tamil Nadu (bottom row) – in both the 1970s (left column) and the 2000s (right column).
Figure 11: Covariance matrix of yields: Examples

Notes: This figure shows the co-variance of (log) yields across crops for two example districts – Chittargarh, Rajasthan (top row) and Madurai, Tamil Nadu (bottom row) – in both the 1970s (left column) and the 2000s (right column).
Figure 12: Crop choice over time: Examples

Notes: This figure shows the allocation of land for two example districts – Chittargarh, Rajasthan (top row) and Madurai, Tamil Nadu (bottom row) – in both the 1970s (left column) and the 2000s (right column).