Volatility and the Gains from Trade*

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Abstract

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 falling trade costs increased farmer's revenue volatility, causing farmers to shift production toward crops with less risky yields. We then characterize how volatility affects farmer's crop choice using a portfolio choice model where returns are determined in general equilibrium by a many-location, many-good Ricardian trade model with flexible trade costs. 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. While the expansion of the Indian highway network would have increased the volatility of farmer's real income had their crop choice remained constant, by changing what they produced farmers were able to avoid this increased volatility and amplify the 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 empirical importance of the relationship between trade and volatility. In particular, does volatility magnify or attenuate the gains from trade and how do agents respond to changes in the risk they face arising from falling trade costs?

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 by reducing the responsiveness of local prices to local rainfall, causing farmers to shift production toward crops less volatile yields. We then incorporate a portfolio allocation model—where producers optimally allocate resources across risky production technologies—into a many country, many good, 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 the second moment welfare effects of trade. Structural estimates suggest that farmers are able to avoid an increase in volatility from falling trade costs by reallocating their production toward less risky crops, thereby amplifying the gains from trade compared to an endowment model of trade.

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 realized 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—who comprise more than three quarters of the economically active population—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, in part, to expansions of the Indian highway network and reductions in tariffs) has amplified the risk faced by farmers. As the The New York Times writes:

> "When market reforms were introduced in 1991, the state scaled down subsidies 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." ("After Farmers Commit Suicide, Debts Fall on Families in India", 2/22/2014).

These concerns, and the importance to policymakers of better understanding the link between trade and volatility, are encapsulated by the fact that the entire Doha round of global trade negotiations collapsed in 2008 (and remains stalled today) precisely because of India and China's insistence on special safeguard mechanisms to protect their farmers from excessive price volatility.

Using a dataset containing the annual price, yield, and area planted for each of 15 major crops across 308 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 document three stylized facts. First, reductions in trade costs due to the expansion of the highway network raised the volatility of nominal income (but not the price index). Second, this increase in volatility occurred because reductions in trade costs reduced the elasticity of local prices to local supply shocks. Third, in response to this changing risk profile, farmers changed what they produced, reallocating land toward crops with higher average yields (as traditional trade models predict) and to crops with less volatile yields (to reduce the volatility the face), although the reallocation toward less volatile crops was less pronounced in districts where farmers had 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. To circumvent the familiar difficulties arising from corner solutions for prices nd patterns of specialization, 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—consistent with mechanism highlighted by the second stylized fact—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 incorporate volatility in the model, we assume that producers allocate their factor of production across crops prior to the realization of productivity shocks. By combining our Ricardian trade model with tools from the portfolio allocation literature (see e.g. Campbell and Viceira (2002)), we are able to derive 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. The model remains sufficiently tractable to yield comparative statics consistent with the three stylized facts detailed above and to analytically characterize the welfare effects of trade.

Finally, we estimate the model and empirically quantify the second moment effects of trade. The tractability of the model allows us to recover key model parameters from the data in a transparent manner. First, the model implies that the unobserved trade costs determine the elasticity of local prices to yield shocks in all locations. Conveniently, this relationship can be reduced to a linear equation and so we can recover unobserved trade costs via ordinary least squares. In particular, we find that expansion of the highway network not only decreased the responsiveness of local prices to local yields (as already shown in the second stylized fact) 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. Second, farmers' unobserved risk-return preferences shape the gradient of the mean-variance frontier at the farmers' observed crop choice. As above, we show that estimates of risk-return tradeoffs can be inferred from these observed choices via ordinary least squares. Reassuringly, the resulting estimates are strongly correlated with spatial and temporal variation in access to rural banks (which, by providing access to a risk mitigating technology, should make farmers act less risk averse).

We use these parameter estimates to quantify the welfare effects of the expansion of the Indian highway network. We find that had farmers' crop allocation remain unchanged, the increased volatility caused by the expansion of the highway network would have offset approximately 15 percent of the first moment gains from trade. However, by changing what they produce, farmers are able to fully hedge against the increased risk, increasing the total gains from trade by appropriately 40 percent over the baseline where crop allocations are held constant. However, the gains from trade varied substantially across India, with districts that experienced above median improvements in market access seeing welfare increases almost three times as large as those below the median.

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—i.e. good-location specific productivity shocks—and trade.

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 an empirical strategy that studies the relationship between famines and railroads in colonial India.[1] 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 two distinct contributions relative to these papers. First, we depart from the Eaton and Kortum (2002) framework and develop an alternative quantitative general equilibrium framework that allows us to analyze the pattern of trade for a finite number of homogeneous goods. Second, by embedding a portfolio allocation decision where real returns are determined in a general equilibrium trade setting, we theoretically characterize the endogenous response of agents to trade-induced changes in their risk profile; and empirically validate that farmers are indeed responding as predicted and that these responses substantially amplify the gains from trade.

The paper is also related to a growing literature applying quantitative trade models to the study of agriculture. Sotelo (2013) and Costinot, Donaldson, and Smith (2014) examine how trade affects crop choice using an Eaton and Kortum (2002) framework, where locations grow multiple crops due to the heterogeneity in the productivity of different plots (in contrast to wanting to diversify against risk, as in our model). As in Costinot and Donaldson (2011), we use farmers' observed crop allocation to identify important unobservables in the model (farmers' risk aversion in our context, prices in their context).

[1]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).

As in Allen (2014), we relax the traditional no-arbitrage condition, although rather than allowing information frictions, we incorporate heterogeneous trade costs.

Finally, 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, see e.g. Fafchamps (1992); Rosenzweig and Binswanger (1993); Kurosaki and Fafchamps (2002). Second, there is also a substantial development literature examining the effect that access to formal credit has on farmers, see e.g. Burgess and Pande (2005) and Jayachandran (2006). Consistent with both strands of literature, we find that better access to rural banks is associated with farmers allocating their resources toward more risky portfolios.

The remainder of the paper is organized as follows. In Section 2, we describe the empirical context and the data we have assembled. Section 3 presents three 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

2.1 Rural India over the past forty years

This paper focuses on rural India over a forty year period spanning 1970 to 2010. 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. (Note that the majority of rural households derive income from agriculture; 85 percent of the rural workforce was in agriculture in the 1971 Census and 72 percent in the 2011 Census.) 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.[2] 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)).[3] The

[2]These figures (and the HYV ones below) come from the 1970-2009 change in area under irrigation (under HYV crops) among districts in the ICRISAT VDSA data introduced in the next section.

[3]As reported in Basu (2006), the share of rural household debt from banks rose from 2.4 percent to 29 percent between 1971 and 1991. By 2003, 44 percent of large farmers (more than 4 acres, accounting for 55 percent of India's agricultural land), 31 percent of small farmers (1-4 acres, 40 percent of land) and 13 percent of marginal farmers (less than 1 acre, 15 percent of land) had an outstanding loan from a formal bank.

availability of credit helped farmers smooth income shocks and so provided a form of insurance.[4]

The third set of changes relate to reductions in inter- and particularly intra-national trade costs. The reductions were driven by two types of national policy change. The first, that we will exploit extensively in the empirical analysis, were major expansions 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'.[5] 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.[6] The second policy change was the broad economic liberalization program 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). This paper focuses on the inter-state and inter-district trade that constituted the overwhelming majority of India's agricultural trade over our sample period, in effect treating India as a closed economy.[7]

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[8] and crop yields come from

[4]India also has a subsidized crop insurance scheme. However, even today coverage is limited, with only 6 percent of farmers voluntarily purchasing cover (a further 11 percent of farmers have agricultural loans with mandatory insurance requirements, see Mahul, Verma, and Clarke (2012)).

[5]See 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.

[6]These figures are Indian government estimates from the 10th, 11th and 12th five-year-plans.

[7]Focusing on the three most traded products—rice, sugar and wheat—external trade (international exports plus imports) equaled 0.5, 0.3 and 11 percent of production by weight in the 1970s, and 2.8, 0.7 and 3 percent in the 2000s, respectively. Unfortunately, India only records internal trade by rail, river and air (recall road accounted for between one and two thirds of freight); and then only for trade between 40 or so large trading blocks in India. Using the rail, river and air data that likely severely underestimate inter-district trade, internal trade equaled 3.8, 1.3 and 21.4 percent of production by weight in the 1970s, and 10.2, 0.9 and 16.3 percent in the 2000s.

[8]These are producer prices—i.e. the farm gate price a farmer receives. India has a system of minimum support prices (MSPs) which, if binding, affect the farm gate price and potentially attenuate any price response our theory will predict. Appendix figures 5-8 plot the distribution of log prices alongside the MSPs for applicable crops for 1970, 1980, 1990 and 2000. There is little evidence of price heaping just at or above the MSPs, as well as substantial mass below the MSPs, suggesting any attenuation from excluding MSPs from our model is limited.

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 308 districts from the 1966-67 crop year all the way through to the 2009-10 crop year.[9] The dataset uses 1966 district boundaries to ensure consistency over time and covers districts in 19 States (containing 95 percent of India's population in the 2001 Census).

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.[10]

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).

Consumer Preferences: Consumption data come from the National Sample Survey (NSS) Schedule 1.0 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 present three sets of stylized facts. The first fact documents an explicit link between trade costs and farmer income: reductions in trade costs induced by the expansion of the Indian highway system raised the volatility of nominal income but not the price index. We then explore the mechanisms that will deliver these predictions in our theoretical model. The second fact provides evidence for the central link between trade costs and volatility in our model: reductions in trade costs reduced the elasticity of local prices to local quantities thereby raising revenue volatility for farmers. The third fact

[9]The 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. The data coverage across crops with districts is good: in the median district-decade pair, we observe at least one year of production data for 13 of the 15 crops and at least one year of price data for 11 of the 15 crops. The data are at the annual level and combine both the rabi and kharif cropping seasons.

[10]See Allen and Arkolakis (2014) for a previous application of the Fast Marching Method to estimate trade costs. The results that follow are similar for alternative assumptions in the construction of the speed images; see below.

provides evidence that farmers respond by making risk-reducing crop choices consistent with a portfolio choice model: reductions in trade costs led farmers to move into crops with higher means (a first-moment effect) and less risky yields (a second-moment effect), with the latter effect attenuated by greater access to rural banks.

3.1 Income volatility and trade costs

Stylized Fact 1A: The volatility of nominal income increased over time

As discussed in Section 2.1, the period between 1970 and 2010 saw large reductions in trade costs within India. Did this period of reductions coincide with a rise in the variance of income? To explore this question, we calculate for each district and decade the mean and variance of nominal (gross) income using annual data on agricultural revenues per hectare.[11] Of course, these are gross of crop costs which may be changing over time—an issue we confront head on in the structural estimates. While these revenues are deflated by the all-Indian CPI, a national price index cannot capture local variation in agricultural prices that play an important role in determining the gains from trade on the consumption side. Accordingly, we also calculate an explicit CES price index for the 15 crops in our sample, with real income being the ratio of nominal income and this price index.[12] Figure 2 plots the log changes in the decade-level mean and variance of each of these three variables compared to the base decade, the 1970s (averaging over districts).

Consistent with reductions in transport costs generating standard first-moment gains from trade, decade-district means of real income rose over time due to increases in nominal incomes and reductions in the price index. However, there were second moment effects as well. Consistent with the literature (e.g. Newbery and Stiglitz (1984)), nominal income became more volatile (since producers faced more revenue risk) and the price index stabilized (since consumers faced less consumption risk). In net, real income became more volatile.

Stylized Fact 1B: The volatility of nominal income increases with market access

Given the myriad of changes over this period, the link between the reduction in trade barriers and the real income trends documented above is, at best, suggestive. We now es-

[11]This paper focuses on the effects of yield volatility across years. Within a year, the timing of the harvest and farm- or micro-region-specific crop failures present additional sources of volatility. Data limitations—the Indian government produces statistics only at the district-year level—preclude us from examining these additional sources of volatility empirically. (Idiosyncratic risk may also be less important if farmers engage in risk sharing arrangements with other farmers in the same location as in Townsend (1994)).

[12]We obtain the CES parameters from a regression of log expenditure shares on log prices and district fixed effects using the 1987/88 NSS household surveys and assume preferences are identical across locations and time periods. As these parameter estimates are used primarily in the structural estimates, we describe the exact specification in Section 5.1 and show the estimated parameters in Table 4.

tablish a more direct link by calculating district-decade level measures of trade openness from the digitized road maps described in Section 2.2. Recall the digitized maps allow us estimate the bilateral travel time between any two points in India in any year. 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:

$$MA_{it} = \sum_{j}^{J} \left(\frac{1}{travel\ time_{ijt}^{\phi}}\right) Y_{jt}$$

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 ϕ we draw on the gravity literature that regresses log trade flows on log distance to estimate how quickly trade flows decline with distance. Following the meta-analyses of Disdier and Head (2008) and Head and Mayer (2014), we set $\phi = 1.5$—the average gravity coefficient for developing country samples—in our preferred market access specification.[13] We also consider $\phi = 1$, a natural benchmark and close to the average of 1.1 found for the all country sample, as well as alternate estimates of the off-highway speed of travel (1/4 of that on the highway rather than 1/3) for robustness.

With these measures in hand, we regress the log of either the mean or the variance of one of the three income measures (nominal income, the price index, and real income) at the district-decade level on one of the three variants of the market access measure. These result are shown in the top panel of Table 1, with each cell the coefficient from a separate regression. All regressions include district and decade fixed effects (and hence identify off differences within districts over time controlling for trends using time changes in other districts).

The results are broadly consistent with the crude inference drawn from the aggregate trends above. We find that the mean of real income rises significantly with all three measures of market access (Column 5). This comes about through a rise in nominal income (Column 1) that far exceeds the rise in the price index (Column 3). Turning to second-moment effects, nominal income becomes significantly more volatile with market access (Column 2). In terms of magnitudes, a rise in market access equal to the median change in

[13] Head and Mayer (2014) perform a meta-analysis of gravity estimates and report an average coefficient on log distance of -1.1 across 159 papers and 2,508 regressions. Head and Mayer (2014) build off an earlier meta-analysis by Disdier and Head (2008) which reports that estimates based on developing country samples are lower 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).

district-level market access between 1970 and 2009 raises the mean of nominal income by 37 percent and the variance of nominal income by 51 percent. In contrast to the increase in the volatility of nominal income, the volatility of the price index is unchanged (Column 4), with real income volatility rising on net (Column 6).

In order for these coefficients to be interpreted as causal, we require that road building does not respond to changes in the means and variances of incomes after controlling for location and time fixed effects. Endogeneity concerns are mitigated by the fact that, as we detail in Section 2.1, much the highway construction was part of centrally-planned national programs designed to connect larger regions. However, worries remain, which in part motivates out structural estimates which allow us to isolate the impacts of trade cost reductions on welfare.

3.2 The responsiveness of prices to quantities and trade costs

Stylized Fact 2: The elasticity of price to quantities declines with market access

We now turn to providing direct evidence for the increased responsiveness of local prices to local supply shocks that links trade costs reductions to the increased nominal income volatility we found in Stylized Fact 1B. To obtain a scale-invariant measure of responsiveness, we calculate the elasticity of local prices to local quantities as follows:

$$\ln p_{igtd} = \beta_{igd} \ln q_{igt} + \delta_{itd} + \delta_{gtd} + \delta_{igd} + \nu_{igdt}, \tag{1}$$

where $\ln p_{igtd}$ is the observed local price in district i of good g in year t in decade d, $\ln q_{igt}$ is the observed production, and β_{igd} is the elasticity. To control for confounds, we include three sets of fixed effects: a district-year fixed effect that controls for the aggregate income of the district in that year; a crop-year fixed effect that controls for changes in the world price of the good; and a district-crop-decade fixed effect that controls for slow-moving changes in crop-specific costs, in the area allocated to the crop, or in crop-specific costs. Identification of β_{igd} can be achieved via ordinary least squares as long as the variation in the production (determined by yields and pre-yield-realization planting choices) of good g in district i in time t is uncorrelated with the residual. Since production may be driven by demand shocks as well as supply shocks , we instrument for quantities using local variation in rainfall.

With these measures in hand, we regress the estimated elasticity of price to production (at the crop-district-decade level) on market access (at the district-decade level, the level we cluster the standard errors at). The regression results are shown in Table 2. The first column also includes crop-district fixed effects while subsequent columns additionally include crop-decade fixed effects (and hence identify off differences within districts over time controlling for crop-specific trends using time changes in other districts). Column 2 presents our main specification, column 3 uses the uninstrumented elasticity estimate, and columns 4 and 5 use the two alternative market access measures.

Across all five columns, the elasticity of local prices to local production increased significantly—from negative values towards zero—with improvements in market access. In terms of magnitudes, using our preferred specification in column 2, a rise in market access equal to the median 1970-2009 change in district-level market access raises the elasticity by 0.022 (from a mean in the 1970s of -0.043). Once again, in order for the coefficients on market access to be interpreted as causal we require that road building does not respond to changes in the covariances of production and prices after controlling for location and time effects. This assumption seems more plausible in this case than it was for the mean of nominal incomes, but caution is still warranted. In summary, we find a weakening of the inverse relationship between local prices and productivities as trade costs fell, the key mechanism in our model through which trade costs affect volatility.

3.3 Crop choices and trade costs

Stylized Fact 3A: Farmer cropping decisions reduce the volatility of nominal income

We expect farmers to respond to the increased elasticity of price to quantities, and the corresponding increase in revenue volatility, by altering their cropping choices to reduce the risk they face. Suggestive evidence for this response comes from repeating the exercise in Stylized fact 1B but calculating nominal revenues using the 1970s crop allocations rather than the actual crop allocations. The bottom panel of Table 1 reports these results. If farmers mitigate the nominal income volatility they face through their planting decisions, we would expect volatility to be higher under the initial (i.e. 1970s) crop allocations than under the actual crop allocations. Comparing Columns 2 and 8 provides support for this hypothesis, with nominal income volatility increasing more under 1970s allocations for two of the market access measures and almost unchanged for the third. Conversely, the mean of nominal income rises less under 1970s allocations. We observe similar patterns for real income. These increases in volatility and reductions in the mean are consistent with farmers making crop choices to be on the mean-variance frontier of real returns.

Stylized Fact 3B: Crop choice responds to the mean and variance of the yield

We now explore the planting decisions themselves to provide more direct evidence for the portfolio choice model underlying the responses above. Different crops 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. Equally important are the covariances of yields across crops which allow farmers to hedge production risk in one crop by planting another crop that can survive under the agroclimatic or pest conditions which cause the first crop to fail. Appendix Figures 9, 10, and 11 highlight this heterogeneity in means, variances, covariances, and crop choice across decades and districts.

Farmers respond to this heterogeneity in the ways modern portfolio theory would predict. Column 1 of Table 3 regresses crop choice (θ_{igd}, the decade-d-average fraction of total area planted with good g in district i) on the log mean yield, $\log \mu^y_{igd}$, and the log variance of yield, $\log v^y_{igd}$, for that district-crop-decade:[14]

$$\theta_{igd} = \beta_1 \log \mu^y_{igd} + \beta_2 \log v^y_{igd} + \gamma_{gd} + \gamma_{id} + \gamma_{ig} + \varepsilon_{igd}$$

This specification can be seen as reduced form—i.e. a regression of an endogenous variable, crop choice, on exogenous ones, the mean and variance of crop yields. (Our theoretical framework in Section 4 will provide such a mapping from the mean and variance of yields to crop choice). We saturate the model by including crop-decade, district-decade, and district-crop fixed effects. These control for both national crop-specific trends and persistent differences in local agroclimatic conditions that could potentially be related to local agricultural technologies and hence bias the β coefficients. To further allay worries about endogenous movements in yields, Appendix Table 9 reports similar results when we instrument for the mean and variance of yields with the mean and variance of yields as predicted by rainfall variation and district-crop fixed effects (allowing coefficients on rainfall to vary by crop, state and decade).

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.[15]

Stylized Fact 3C: Farmers move into less-risky portfolios when market access increases

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 (the main effect of market access is swept out by the district-decade fixed effects):

$$\theta_{igd} = \beta_1 \log \mu^y_{igd} + \beta_2 \log v^y_{igd} + \beta_3 \log \mu^y_{igd} \times MA_{id} + \beta_4 \log v^y_{igd} \times MA_{id} + \gamma_{gd} + \gamma_{id} + \gamma_{ig} + \varepsilon_{igd}$$

[14] As crop choices are not independent, standard errors are clustered at the district-decade level.

[15] In terms of magnitudes, a 10 percent increase in the mean yield raises the fraction of land planted with a crop by 0.0004, while a 10 percent increase in the variance of the yield reduces the fraction of land planted by 0.0001.

The regression coefficients are shown in column 2 of Table 3. We find a significant positive β_3 coefficient and a significant negative β_4 coefficient. Reductions in trade costs, and hence increased market access, led farmers to further increase the share of land allocated to high yield crops and further reduce the share allocated to high variance crops. In terms of magnitudes, a rise in market access equal to the median 1970-2009 change in district-level market access approximately doubles the responsiveness to changes in the mean and variance of yields. Similar results obtain for the two other market access measures in columns 4 and 6, and when we instrument for the yield terms and their interactions with predicted yields using rainfall and interactions in Appendix Table 9.

These findings are consistent with farmers responding to the reduced responsiveness of price to quantities highlighted in Stylized Fact 2—and the resulting reduction 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 trade allows (a first-moment effect—essentially farmers can now allocate more land to the most productive crops).

Stylized Fact 3D: Bank access attenuates the movement into less risky portfolios

Finally, we take the previous specification and include additional 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 and 7 of Table 3. The triple interaction of the log variance of yields, banks and market access is positive and significantly different from zero using all three 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.[16]

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 location Ricardian trade model with a finite number of homogenous goods and arbitrary (symmetric) bilateral trade costs. We circumvent difficulties due to corner solutions by assuming trade costs are heterogenous which yields tractable expressions for equilibrium prices and patterns of specialization across locations. Importantly for the task at hand, this framework allows us to incorporate volatility by applying tools from the portfolio allocation literature. We show that the

[16]As shown in Appendix Table 9, the instrumentation strategy used for facts 3B and 3C does not work in this case as the first stage is too weak when we create 8 instruments for the 8 exogenous variables using predicted yields and interactions.

entire model remains sufficiently tractable to yield both qualitative predictions consistent with the stylized facts above as well as structural estimating equations that will allow us to quantify how volatility affects the gains from trade in Section 5.

4.1 Model setup

Geography

The world is composed of a large number of villages (indexed by $i \in \{1, ..., N\}$). All pairs of villages are separated by trade costs. Each village $i \in \{1, ..., N\}$ is inhabited by a measure L_i of identical farmers, who produce and consume goods in village i.

Production

There are a finite number of G homogenous goods ("crops") that can be produced in each village i. Land is the only factor of production. Each farmer in each village is endowed with a unit of land and chooses how to allocate her land across the production of each of the G goods.[17] Let θ_{ig}^{f} denote the fraction of land farmer f living in location i allocates to good g, where the farmer's land constraint is $\sum_{g=1}^{G} \theta_{ig}^{f} = 1$. In what follows, we refer to $\left\{\theta_{ig}^{f}\right\}_{g}$ as farmer f's crop choice.

Production is risky. In particular, let the (exogenous) productivity of a unit of labor in village i for good g be $A_{ig}(s)$, where $s \in S$ is the state of the world. We abstract from idiosyncratic risk and assume that all farmers within a given village in a particular state of the world face the same yields for all goods.[18] Given her crop choice, the nominal production income farmer f receives in state $s \in S$ is:

$$Y_i^f(s) = \sum_{g=1}^{G} \theta_{ig}^{f} A_{ig}(s)\, p_{ig}(s), \tag{2}$$

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

Preferences

Farmer f in location i receives utility $U_i^f(s)$ in state s where the utility function displays constant relative risk aversion governed by parameter $\rho_i > 0$ over a constant elas-

[17] We abstract from the dynamic aspect of crop choice due to, for example, switching costs as in Scott et al. (2013). In the quantitative analysis, we examine the change in crop allocations across decades rather than years, mitigating this concern.

[18] 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 Townsend (1994).

ticity of substitution (CES) aggregate of goods:

$$U_i^f(s) \equiv \frac{1}{1-\rho_i}\left(Z_i^f(s)\right)^{1-\rho_i}, \tag{3}$$

where $Z_i^f(s) \equiv \left(\sum_{g=1}^{G} \alpha_g^{\frac{1}{\sigma}} c_{ig}^f(s)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}$ is a CES nest across goods, $c_{ig}^f(s)$ denotes the quantity consumed of good g in state s and $\alpha_g > 0$, $\sum_{g=1}^{G} \alpha_g = 1$ is a demand shifter for good g.

Consistent with Mukesh Eswaran (1990), we interpret the risk aversion parameter ρ_i as the "effective risk aversion" which combines both innate risk preferences of the farmer and any access the farmer has to ex-post risk mitigating technologies (savings, borrowing, insurance, etc.).[19]

Trade

As in many trade models, we assume that equilibrium prices are consistent with a large number of traders who face iceberg trade costs and engage in price arbitrage across locations. Rather than assuming that all traders face the same costs, however, we instead assume that traders are heterogeneous in their trading technology and capacity constrained. As a result, the standard no-arbitrage equation—that the ratio of any two prices is bounded above by the iceberg trade cost–no longer holds as many traders of various efficiencies engage in price arbitrage. Instead, an alternative no-arbitrage equation holds, equation (8) below, which has a convenient log-linear form and the intuitive property that more goods flow toward destinations with higher relative prices. We now describe the trading process that micro-founds this key arbitrage equation. We note that alternative micro-foundations, or simply asserting the arbitrage equation, would allow us to generate equilibrium patterns of specialization and incorporate volatility in a tractable manner. For example, in Appendix A.2 we show that the arbitrage equation can also arise from a setup where iceberg trade costs are increasing and convex in the quantity shipped between two locations

We assume the following trading process. Every farmer wishing to sell a good is randomly matched to a "selling" trader and every farmer wishing to buy a good is randomly matched to a "buying" trader. Consider first the case of a farmer wishing to sell some quantity of good g. The "selling" trader she is matched to pays the farmer the local market price $p_{ig}(s)$ and then decides whether to sell the good locally or export it. If the trader decides to sell the good locally, he sells it for $p_{ig}(s)$, making zero profit. If the trader de-

[19] In Appendix A.1, we provide a micro-foundation for this interpretation where farmers can purchase insurance from local perfectly competitive money-lenders.

cides to export the good, he sells it to a centralized shipper for the maximum price net of the trade costs across all destinations to which the trader could have sold. The process works in reverse for a farmer wishing to buy some quantity of good g: she buys for the local price $p_{ig}(s)$ from a "buying" trader prior to which the trader decides whether to import the good or source it locally. If the trader decides to source it locally, he pays $p_{ig}(s)$, earning zero profit. If he decides to import the good, the trader buys the good from the centralized shipper for the minimum price net of the trade costs across all origins from which the trader could have bought.

We assume the probability that a randomly matched trader is able to buy a unit of good from $i \in \{0, ..., N\}$ and sell it to $j \in \{0, ..., N\}$ (or vice versa) with a bilateral ad valorem trade cost less than $\bar{\tau}$ is Pareto distributed with shape parameter $\varepsilon_{ij} \in (0, \infty)$:

$$\Pr\left\{\tau_{ijg} \leq \bar{\tau}\right\} = 1 - \left(\frac{b_g}{\bar{\tau}}\right)^{\varepsilon_{ij}}.$$

The greater the value of the shape parameter ε_{ij}, the lower the bilateral trade costs (in particular, as $\varepsilon_{ij} \to 0$ trade becomes infinitely costly and as $\varepsilon_{ij} \to \infty$ trade becomes costless). We assume the shape parameter is bilaterally symmetric, i.e. $\varepsilon_{ij} = \varepsilon_{ji}$. The scale parameter—$b_g = \varphi_g(s)$ for "selling" traders and $b_g = 1/\varphi_g(s)$ for "buying" traders—determines whether it is relatively more costly to trade when exporting or importing. The good- and state-specific (endogenous) scalar $\varphi_g(s)$ captures the equilibrium "market tightness" and ensures markets clear. Intuitively, if there are more selling traders attempting to export a good than buying traders attempting to import, a $\varphi_g(s) > 1$ acts as a tax on selling traders and a subsidy on buying traders. This induces more buying traders to import, while causing marginal selling traders to prefer to sell locally, thereby clearing the market. We assume that traders' 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). Finally, because traders earn arbitrage profits in this setup, for simplicity we assume that all trading profits are redistributed back to farmers proportionally to their production income, with the proportion denoted by $\phi(s)$.

There are a several things to note about this setup. First, while we require that farmers both buy and sells goods through traders, because these transactions occur at the local market price, a farmer happy to do so.[20] Second (and relatedly), while we require that

[20]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. Because farmers cannot directly trade with other districts (and trader income is redistributed proportionally to total income), farmer income depends only on local equilibrium prices,

traders sell their goods to a centralized shipper rather than transact directly with other locations, because these transactions occur at the best price a trader could have received, a trader is happy to do so. (The centralized shipper is also happy with this price, as it maximizes its own surplus from the transaction.) The centralized shipper act as a clearing house for all imports and exports of a good, allowing us to rely on standard market clearing conditions to solve for equilibrium market tightness. This assumption, however, does come at a cost: as in a standard Ricardian trade model with more than two locations, only total net exports for each location-good pair are pinned down in equilibrium with bilateral trade flows indeterminate.

4.2 Trade and equilibrium prices

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

$$p_{ig}(s)\, C_{ig}(s) = \frac{\alpha_g \left(p_{ig}(s)\right)^{1-\sigma}}{\sum_h \alpha_h \left(p_{ih}(s)\right)^{1-\sigma}} Y_i(s)\left(1+\phi(s)\right), \tag{4}$$

where $C_{ig}(s) = L_i c^f_{ig}(s)$ is the total quantity of g consumed in a location i and $Y_i(s) = L_i Y^f_i(s)\left(1+\phi(s)\right)$ is the total income in location i. On the production side, $Q_{ig}(s) = L_i \theta_{ig} A_{ig}(s)$ is the total quantity produced of good g in village i, where we omit the "f" superscript for the village level land allocation; since faremrs are homogeneous, in equilibrium $\theta^f_{ig} = \theta_{ig}$ for all f.

We now consider how the arbitrage behavior of traders affects the relationship between production and consumption in each village. Market clearing requires that the the quantity consumed of good g in village i that is also produced in village i must be equal to quantity produced of good g in village i that is also consumed in village i:

$$C_{ig}(s) \times \Pr\{\text{sourced locally}\} = Q_{ig}(s) \times \Pr\{\text{sold locally}\} \tag{5}$$

A "buying" trader chooses to source a good locally rather than import that good only if the local price is at least as low as any origin price net of trade costs. Because there are a continuum of farmers each randomly matched to a trader, the law of large numbers implies the fraction of the quantity consumed of good g in village i that is sourced locally is equal to the probability that a "buying" trader's trade costs are such that sourcing locally

which simplifies the determination of the optimal crop choice.

is cheapest:

$$\Pr\left\{\text{sourced locally}\right\} = \Pr\left\{p_{ig}\left(s\right) \le \min_{j\in\{0,\dots,N\}} \tau_{ji} p_{jg}\left(s\right)\right\} \iff$$

$$= \prod_{j\neq i}\left(\left(\frac{p_{jg}\left(s\right)}{p_{ig}\left(s\right)}\frac{1}{\varphi_g\left(s\right)}\right)^{\varepsilon_{ji}}\right)^{\mathbf{1}\left\{p_{jg}(s)\le p_{ig}(s)\varphi_g(s)\right\}}, \tag{6}$$

where $\mathbf{1}\left\{\cdot\right\}$ 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, a "selling" trader chooses to sell a good locally rather than exporting the good only if the local price is at least as high as any destination price net of trade costs. Again invoking the law of large numbers, the fraction of the quantity produced of good g in location i that is sold locally is equal to the probability that the trade costs are such that selling locally is most profitable:

$$\Pr\left\{\text{sold locally}\right\} = \Pr\left\{p_{ig}\left(s\right) \ge \max_{j\in\{0,\dots,N\}} \frac{p_{jg}\left(s\right)}{\tau_{ij}}\right\} \iff$$

$$= \prod_{j\neq i}\left(\left(\frac{p_{ig}\left(s\right)}{p_{jg}\left(s\right)}\varphi_g\left(s\right)\right)^{\varepsilon_{ij}}\right)^{\mathbf{1}\left\{p_{ig}(s)\varphi_g(s)\le p_{jg}(s)\right\}} \tag{7}$$

Together, equations (5), (6), and (7) along with symmetric bilateral distributions provide the following no-arbitrage condition where the ratio of local consumption and production is the product of the ratio of the local price to prices elsewhere:

$$\frac{C_{ig}\left(s\right)}{Q_{ig}\left(s\right)} = \prod_{j\neq i}\left(\frac{p_{ig}\left(s\right)}{p_{jg}\left(s\right)}\varphi_g\left(s\right)\right)^{\varepsilon_{ij}}. \tag{8}$$

Intuitively, equation (8) states that the higher the price of a good in a village relative to all other villages, the more of the good will flow into the village relative to how much flows out (i.e. the village will consume more of a good relative to how much it produces). As mentioned above, all the results that follow are consistent with any alternative setup delivering the no-arbitrage equation (8).

Substituting the demand equation (4) into equation (8) and solving the log-linear system of equations, we obtain the following expression for equilibrium prices:

$$p_{ig}\left(s\right) = \alpha_g^{\frac{1}{\sigma}} \prod_{j=1}^{N}\left(\frac{D_j\left(s\right)}{Q_{jg}\left(s\right)}\varphi_g\left(s\right)^{-\bar{\varepsilon}_j}\right)^{T_{ij}}, \tag{9}$$

where $D_i\left(s\right) \equiv \frac{Y_i(s)(1+\phi(s))}{\sum_h \alpha_h (p_{ih}(s))^{1-\sigma}}$ is equilibrium aggregate demand,$\bar{\varepsilon}_i \equiv \sum_{j\neq i}\varepsilon_{ij}$, $\mathbf{T} \equiv \mathbf{E}^{-1}$, where $\mathbf{E}$ is the $N \times N$ matrix with $E_{ij} = -\varepsilon_{ij}$ for $i \neq j$ and $E_{ii} = \sigma + \bar{\varepsilon}_i$ for all $i \in \{1, ..., N\}$. Equation (9) implies that the partial elasticity of the price of good g in village i to the quantity produced in village j is T_{ij} (conditional on the aggregate demand $D_j(s)$ and the market tightness $\varphi_g(s)$), i.e.:

$$-\frac{\partial \ln p_{ig}(s)}{\partial \ln Q_{jg}(s)} = T_{ij}.$$

Intuitively, how responsive the price in one location is to a productivity shock in another location depends not only on the trade costs between those two locations, but on the full geography of the system.

There are two notable properties of the price elasticities. First, because $\mathbf{E}$ is diagonally dominant with strictly positive elements on the diagonal and strictly negative elements off the diagonal, it is an M-matrix, so that its inverse $\mathbf{T} \equiv \mathbf{E}^{-1}$ exists and is itself strictly positive (see conditions F_{13} and N_{39} of Plemmons (1977)). As a result, a positive productivity shock in any location will (weakly) decrease the equilibrium prices in all other locations. Second, because $\sum_{j=1}^{N} E_{ij} = \sigma$, the sum of the elasticity of a price in location i to all production shocks throughout the world is constant and equal to the inverse of the elasticity of substitution: $\sum_{j=1}^{N} T_{ij} = \frac{1}{\sigma}$. In autarky (when $\varepsilon_{ij} = 0$ for all $j \neq i$), the elasticity of the local price to local production shocks is $\frac{1}{\sigma}$ and not responsive to production shocks elsewhere. With free trade (i.e. as $\varepsilon_{ij} \to \infty$ for all $j \neq i$), the elasticity of the price in village i is equally responsive to production shocks throughout the world (with an elasticity $\frac{1}{\sigma N}$). More generally, as trade costs fall, local prices become less responsive to local production shocks and more responsive to production shocks elsewhere (closely related to Stylized Fact 2, and a prediction we will formalize in Section 4.5).

Finally, given the vector of quantities produced of each good in each location in state s, equilibrium profits of traders $\phi(s)$ and the market tightness $\varphi_g(s)$ are determined in general equilibrium by the aggregate goods market clearing condition:

$$\sum_{i=1}^{N} C_{ig}(s) = \sum_{i=1}^{N} Q_{ig}(s) \;\; \forall g \in \{1, ..., G\} \iff$$

$$\varphi_g(s)^{-\sigma \sum_{j=1}^{N} T_{ij}\bar{\varepsilon}_j} (1 + \phi(s)) = \frac{\sum_{i=1}^{N} Q_{ig}(s)}{\sum_{i=1}^{N} \left(\prod_{j=1}^{N} \left(Q_{jg}(s)\right)^{\sigma T_{ij}} \right) \tilde{D}_i(s)} \; \forall g \in \{1, ..., G\}, \qquad (10)$$

where: $\tilde{D}_i(s) \equiv \frac{\sum_h \alpha_h^{\frac{1}{\sigma}} \varphi_h^{\sum_{j=1}^{N} T_{ij}\bar{\varepsilon}_j} \left(\prod_{j=1}^{N} \left(Q_{jh}(s)\right)^{-T_{ij}} \right) Q_{ih}(s)}{\sum_h \alpha_h^{\frac{1}{\sigma}} \varphi_h^{(1-\sigma)\sum_{j=1}^{N} T_{ij}\bar{\varepsilon}_j} \left(\prod_{j=1}^{N} \left(Q_{jh}(s)\right)^{T_{ij}} \right)^{\sigma - 1}}$. The market tightness parameters $\{\varphi_g(s)\}$ ensure that the ratio of the total quantity produced of each good to the total quantity consumed by farmers in the absence of transfers from traders is equal across all goods; the equilibrium profits of traders $\phi(s)$ then scale consumption upward so that total consumption equals total production.

4.3 Optimal crop choice: no volatility

We now characterize farmers' optimal crop choice. Prior to discussing the general case where productivity is stochastic, it is informative to consider the case where productivity is constant.

In the absence of uncertainty, the return to the farmer per unit of land (i.e. her factor price) must be equalized across all goods she produces[21], i.e.:

$$p_{ig}A_{ig} = w_i \; \forall g \in \{1..., G\}, \tag{11}$$

for some $w_i > 0$. Taking logs and substituting in equation (9) for the equilibrium price and recalling that $Q_{ig} = L_i\theta_{ig}A_{ig}$ yields:

$$\frac{1}{\sigma}\ln\alpha_g + \sum_{j=1}^{N} T_{ij}\ln\left(\frac{D_j}{\theta_{jg}A_{jg}L_j}\varphi_g^{\bar{\varepsilon}_j}\right) + \ln A_{ig} = \ln w_i$$

for some $\ln w_i \in \mathbb{R}$. Solving this system of equations across all villages simultaneously and applying the land constraint $\sum_{g=1}^{G}\theta_{ig} = 1$ yields (see Appendix A.3.1 for the complete derivation):

$$\theta_{ig} = \frac{\alpha_g\varphi_g^{-\bar{\varepsilon}_i}A_{ig}^{\sigma-1}\prod_{j\neq i}\left(\frac{A_{ig}}{A_{jg}}\right)^{\varepsilon_{ij}}}{\sum_{h=1}^{G}\alpha_h\varphi_h^{-\bar{\varepsilon}_i}A_{ih}^{\sigma-1}\prod_{j\neq i}\left(\frac{A_{ih}}{A_{jh}}\right)^{\varepsilon_{ij}}}. \tag{12}$$

Equation (12) provides an 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.[22] All else equal, a country will specialize more in the production of good g the greater its own demand for that good (the α_{ig} term), the greater its productivity of that good as long as goods are substitutes (the $A_{ig}^{\sigma-1}$ term), the lower the relative market tightness for "selling" (the $\varphi_g^{-\bar{\varepsilon}_i}$ term), and the

[21] It is straightforward to show that in equilibrium, all goods will be produced in all locations, as equation (9) implies that the price of a good will go to infinity as the time allocated to that good goes to zero.

[22] Typically in quantitative many-location general equilibrium trade models, the equilibrium patterns of specialization do not admit analytical characterization. For example, in extensions of the Eaton and Kortum (2002) to multiple goods, each of which is a composite of a continuum of varieties, (see e.g. Donaldson (2008), Costinot, Donaldson, and Komunjer (2011), and Costinot and Rodriguez-Clare (2013)), the amount of labor allocated to the production of each good can only be determined by solving a nonlinear system of equations. Intuitively, the reason this setup yields a tractable expression for the equilibrium pattern of specialization is because farmer revenue depends only on local prices, i.e. prices in other locations only affect farmer's crop choice through their equilibrium relationship to local prices. (While farmers do receive revenue from trade, because this revenue is distributed proportionally to total income, it does not affect farmer's crop choice).

greater its comparative advantage in that good (the $\prod_{j \neq i} \left(A_{ig}/A_{jg}\right)^{\varepsilon_{ij}}$ term), all relative to those same terms for all other goods. The greater the Pareto shape parameter ε_{ij} governing the distribution of bilateral trade costs between i and j (i.e. the lower the bilateral trade costs), the more the relative productivity of i and j matters for i's specialization.

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

$$U_i^f = \frac{1}{1-\rho_i} \left(\left(\sum_{g=1}^{G} \alpha_g A_{ig}^{\sigma-1} \right)^{\frac{1}{\sigma-1}} (1+\phi) \right)^{1-\rho_i}.$$

In the absence of volatility, the utility of farmers only depends on trade through the redistributed trader profits (the $1+\phi$ term). As in a standard Ricardian model, opening up to trade increases the returns to goods that a location has a comparative advantage in, 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; 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. Hence, here trade does not affect the relative prices that farmers face nor the income they earn from selling their crops, so welfare is only affected through the income from trader profits.

4.4 Optimal crop choice: with volatility

We now turn to the general case where productivity is subject to shocks (e.g. rainfall realizations) which occur after the time allocation decision has been made (e.g. after planting). With volatility, farmers make their crop choices in order to maximize their expected utility. We first characterize the mapping from the distribution of productivities across states of the world to the distribution of farmer welfare across states of the world. We then characterize the optimal crop choice of a farmer maximizing her expected utility taking prices and the crop choice of other farmers as given. Finally, we derive an analytical expression for the equilibrium crop choice, which is a generalization of equation (12) above.

By substituting the equilibrium price in equation (9) into the indirect utility function coming from the preferences in equation (3), we can write the real returns of farmer f

located in village i in state of the world s as:

$$Z_i^f(s) = \frac{(1+\phi(s)) \sum_{g=1}^{G} \theta_{ig}^f \alpha_g^{\frac{1}{\sigma}} A_{ig}(s) \prod_{j=1}^{N} \left(\theta_{jg} A_{jg}(s) \varphi_g(s)^{-\bar{\varepsilon}_j}\right)^{-T_{ij}}}{\left(\sum_{g=1}^{G} \alpha_g^{\frac{1}{\sigma}} \left(\prod_{j=1}^{N} \left(\theta_{jg} A_{jg}(s) \varphi_g(s)^{-\bar{\varepsilon}_j}\right)^{T_{ij}(\sigma-1)}\right)\right)^{\frac{1}{1-\sigma}}} \tag{13}$$

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 $\mathbf{A}_i(s)$ as the $G \times 1$ vector of $A_{ig}(s)$. Then $\ln \mathbf{A}_i \sim N\left(\mu^{A,i}, \mathbf{\Sigma}^{A,i}\right)$ for all $i \in \{1, ..., N\}$.*[23]

By applying two commonly used approximations—namely a log-linearization of location prices around mean (log) productivity and a second-order approximation implying that the sum of log normal variables is itself approximately log normal (see, e.g. Campbell and Viceira (2002))[24]—we can show that farmer utility is (approximately) log normally distributed. We summarize this result in the following proposition:

Proposition 1. *The distribution of the real returns of farmer f in location i is approximately log-normal, i.e.:*

$$\ln Z_i^f \sim N\left(\mu_i^Z, \sigma_i^{2,Z}\right),$$

where μ_i^Z and $\sigma_i^{2,Z}$ are defined in Appendix A.4.

Proof. See Appendix A.4. □

Because Proposition (1) shows the log real returns $Z_i^f(s)$ are (approximately) log normally distributed, the expected utility of a farmer takes the following convenient form:

$$E\left[U_i^f\right] = \frac{1}{1-\rho_i} \exp\left(\mu_i^Z + \frac{1}{2}(1-\rho_i)\sigma_i^{2,Z}\right)^{1-\rho_i}. \tag{14}$$

[23] We 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.

[24] Campbell and Viceira (2002) use a second order approximation around zero returns, which is valid for assets over a short period of time. Because our time period is a year, we instead approximate around the mean log returns. This comes at a slight cost to tractability, but substantially improves the approximation—in Monte Carlo simulations, we find the approximated expected utility is highly correlated (correlations greater than 0.95) with the actual expected utility.

Because $E\left[Z_i^f\right] = \exp\left(\mu_i^Z + \frac{1}{2}\sigma_i^{2,Z}\right)$, equation (14) 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 ρ_i. As a result, a farmer's optimal crop choice solves the following maximization problem:

$$\max_{\left\{\theta_{ig}^f\right\}} \mu_i^Z + \frac{1}{2}\left(\sigma_i^{2,Z} - \rho_i \sigma_i^{2,Z}\right) \text{ s.t. } \Sigma_{g=1}^G \theta_{ig}^f = 1. \tag{15}$$

Substituting the expressions for μ_i^Z and $\sigma_i^{2,Z}$ from Proposition 1 implies the following first order conditions for all $g \in \{1, ..., G\}$:

$$\mu_g^{z,i} - \rho_i \sum_{h=1}^G \theta_{ih}^f \Sigma_{gh}^{z,i} = \lambda_i, \tag{16}$$

where $\mu_g^{z,i}$ is the marginal contribution of crop g to the log of the mean real returns, $\Sigma^{z,i}$ is the variance-covariance matrix of real returns per unit time across crops,[25] and λ_i is the Lagrange multiplier on the constraint $\sum_{g=1}^G \theta_g = 1$. Equation (16)—which is the generalization of the indifference condition (11) to accommodate uncertainty—is intuitive: a good with a high total variance of real returns (i.e. a high $\sum_{h=1} \Sigma_{gh}^{z,i} \theta_{ih}^f$), must have high real returns (i.e. a high $\mu_g^{z,i}$) to compensate for the additional risk.

It is important to note that the equilibrium real returns for any farmer depend on the crop choice of all other farmers as other farmers' crop choices will affect the equilibrium prices (see equation (38) in the appendix). Just as in the deterministic case, we solve for the equilibrium crop choice across all villages simulatenously by combining the farmer's first order conditions with the expression for log nominal revenue per crop and solve the resulting log-linear system of equations (see Appendix A.3.2 for the full derivation). This yields the following generalization of equation (12) to incorporate production volatility:

$$\theta_{ig} \propto \alpha_g \exp\left(\mu_g^{A,i}\right)^{-1} \bar{\varphi}_g^{-\bar{\varepsilon}_i} b_{ig}^\sigma \prod_{j \neq i} \left(\frac{b_{ig}}{b_{jg}}\right)^{\varepsilon_{ij}}, \tag{17}$$

where $b_{ig} \equiv \frac{\exp\left(\mu_g^{A,i}\right)}{\lambda_i - \left(\frac{1}{2}\Sigma_{gg}^{x,i} - \sum_{h=1}^G \theta_{ih}\left(\Sigma_{gh}^{x,i} - \Sigma_{gh}^{z,i}\right) - \rho_i \sum_{h=1}^G \theta_{ih} \Sigma_{gh}^{z,i}\right)}$ is the *risk adjusted productivity* of farmers in village i producing crop g and the scale is determined by the constraint $\sum_{g=1}^G \theta_{ig} = 1$. Whereas in the absence of volatility, patterns of specialization were determined by the relative productivity of different locations, with volatility, risk adjusted productivity defines

[25] In particular, $\mu_g^{z,i} \equiv \frac{\exp\left\{\mu_g^{x,i}\right\}}{\sum_{g=1}^G \theta_{ig}^f \exp\left\{\mu_g^{x,i}\right\}} + \frac{1}{2}\Sigma_{gg}^{x,i} - \sum_{h=1}^G \theta_{ih}^f \left(\Sigma_{gh}^{x,i} - \Sigma_{gh}^{z,i}\right)$, where the definitions for the vector $\mu^{x,i}$ and variance-covariance matrices $\Sigma^{x,i}$ and $\Sigma^{z,i}$ are presented in Appendix A.4.

comparative advantage and determines the patterns of specialization. As before, trade costs determine the weighting that each location places on its comparative advantage relative to each trading partner.

4.5 Qualitative implications

Explaining the stylized facts

We now show that the model developed above is consistent with the stylized facts presented in Section 3. We summarize the results in the following proposition.

Proposition 2. *Suppose that the Pareto distribution of trade costs can be written as $\varepsilon_{ij}(t) = \varepsilon_{ij} t$, where $t \geq 0$ captures the overall level of openness of the world and an increase in t indicates a fall in trade costs and there are a large number of villages (so that the equilibrium market tightness is constant across states of the world) Then:*

(1) [Stylized Fact #1] Define $\sigma^2_{i,Y}$ and $\sigma^2_{i,P}$ to be the variance of the log of the numerator and the denominator, respectively, of the real returns $Z_i^f(s)$. Then:

$$\frac{d\sigma^2_{i,Y}}{dt}|_{t=0} > 0 \text{ and } \frac{d\sigma^2_{i,P}}{dt}|_{t=0} < 0,$$

i.e. moving from autarky to costly trade increases the volatility of nominal income and decreases the volatility of prices.

(2) [Stylized Fact #2] Any increase in openness decreases the responsiveness of local prices to local yield shocks, i.e.:

$$\frac{d}{dt}\left(-\frac{\partial \ln p_{ig}(s)}{\partial \ln A_{ig}(s)}\right) < 0.$$

(3) [Stylized Fact #3] Any increase in openness causes farmers to reallocate production toward crops with higher mean yields. Moreover, as long as farmers are sufficiently risk averse (i.e. ρ_i is sufficiently large and positive), goods are substitutes (i.e. $\sigma \geq 1$), and local prices are not too responsive to local productivity shocks (i.e. $(1 - T_{ii})\theta_{ig} \geq T_{ii}\alpha_g$), then any increase in openness causes farmers to reallocate production towrad crops with less volatile yields, although the latter effect is attenuated the greater the access to insurance (i.e. the lower ρ_i). Formally for any two crops $g \neq h$:

$$\frac{d}{dt}\frac{\partial\left(\ln\theta_{ig} - \ln\theta_{ih}\right)}{\partial\mu^A_{ig}} > 0,\ \frac{d}{dt}\frac{\partial\left(\ln\theta_{ig} - \ln\theta_{ih}\right)}{\partial\Sigma^{A,i}_{gg}} \leq 0, \text{ and } -\frac{d}{dt}\frac{\partial^2\left(\ln\theta_{ig} - \ln\theta_{ih}\right)}{\partial\Sigma^{A,i}_{gg}\partial\rho_i} \geq 0.$$

Proof. See Appendix A.5.

Intuitively, as trade costs fall, more traders engaging in arbitrage across villages, so that an incease in openness causes local prices to be less responsive to local yields – consistent with Stylized Fact #2. Because local prices are less responsive to local yields, prices rise less in states of the world with low yields, increasing the volatility of nominal income and decreasing the volatility of the price index – consistent with Stylized Fact #1. Finally, consistent with Stylized Fact #3, farmers change their crop choice, balancing traditional gains from specialization by moving into crops with higher average means against efforts to reduce their risk by moving into crops with less volatile yields, with the trade-off governed by their level of risk aversion.. □

Volatility and the gains from trade

We now turn to the welfare implications of the model. We summarize the relationship between welfare, trade costsand volatility in the following proposition:

Proposition 3. *1) Moving from autarky to costly trade (weakly) improves farmer welfare, i.e. the gains from trade are always (weakly) positive. 2) Increasing the volatility of productivity (keeping constant the average productivity) may amplify or attenuate the gains from trade.*

Part (1) of Proposition 3 arises from the standard revealed preference argument for why trade is welfare improving (see, e.g. Dixit and Norman (1980)). Because all farmers in a village are identical, in autarky, each consumes what she produces in all states of the world. With trade, a farmer always has the option to make the same planting decisions; moreover, in any state of the world, because the farmer both buys and sells to traders at the local price, she always has the option to consume what she produces. Hence, in all states of the world, a farmer can always achieve the same level of utility as in autarky, so that across all states of the world, her expected utility must with trade must be at least as great as in autarky.[26]

Parts (2) of Proposition 3 can be illustrated with two simple examples (illustrated in Table 10 of the Appendix). We first show how volatility can amplify the gains from trade. Consider a world of two villages and two crops. Suppose that farmers have Cobb-Douglas preferences over the two goods with equal expenditure shares. Suppose too that the average productivity of each good in each village in the same. Because the two villages are identical, in the absence of volatility there are no gains from trade. Now suppose that the production of good A in village 1 is risky. As discussed above (see equation (**??**)), in autarky farmers in village 1 will allocate an equal amount of labor to the production of both crops even though good A is risky as the unit price elasticity implies that the volatility farmers face is aggregate price index risk. With trade, however, the local price

[26]This is in contrast to Newbery and Stiglitz (1984), where trade can make agents worse off in the presence of volatility. In that paper, agents are not permitted to consume what they produce; instead, they rely on the existence of two types of agents: "farmers" that produce crops an consume a numeraire good, and "consumers" that consume crops and produce the numeraire good. As a result, the autarkic consumption bundle is not necessarily always available to agents.

in village 1 no longer responds one-for-one to the local productivity shock. This allows farmers in village 1 to reduce the risk they face by reallocating production toward good B. Farmers in village 2 benefit by reallocating production toward good A, which now has a higher relative price. Intuitively, by decoupling production and consumption decisions, trade converts the aggregate price index risk farmers would face in autarky into idiosyncratic crop specific risk, allowing farmers allocate their crops in such a way so as to reduce their risk exposure.[27]

However, volatility can also attenuate the gains from trade. As above, consider a world of two village and two crops, where farmers have Cobb-Douglas preferences over the two goods with equal expenditure shares. Suppose that village 1 has a comparative and absolute advantage in good A and village 2 has a comparative and absolute advantage in good B so that in the absence of volatility, there are gains from trade through specialization. Now let us introduce volatility by supposing that the production of good A in village 1 is risky and the production of good B in village 2 is risky. In autarky, farmers in both villages will allocate an equal amount of labor to the production of both goods. With trade, however, if farmers are sufficiently risk averse, they will not specialize in the production of the risky crops despite their respective comparative advantages. As a result, the standard gains through specialization will be smaller, attenuating the total gains from trade.

5 Quantifying the welfare effects of trade and volatility

We now bring the model developed above to the data on rural India to quantify the welfare effects of trade in the presence of volatility. 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 effective risk aversion in each district. Finally, we use the estimates to quantify the welfare effects of trade and volatility 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 preference parameters $\{\alpha_g\}$ and σ, the matrix of shape parameters $\{\varepsilon_{ij}\}_{i\neq j}$ governing trade costs, the effective risk aversion ρ_i in each district and the mean and variance-covariance matrix $\mu^{A,i}$ and $\Sigma^{A,i}$ for the yields of all goods produced (net of production costs). We discuss how we estimate each of these in turn.

[27]Introducing volatility can also amplify the *first moment* gains of trade, as differences in the *realized* productivities in the two countries generate gains from trade, even if the *average* productivities in the two countries are identical.

Estimating the preference parameters from variation in budget shares and prices

We can recover the preference parameters $\{\alpha_g\}$ and elasticity of substitution σ by estimating the CES demand function implied by equation 3:

$$\ln\left(C_{ig}/Y_i\right) = (1-\sigma)\ln p_{ig} - (1-\sigma)\ln P_i + \ln \alpha_g \tag{18}$$

where $P_i = \left(\sum_g \alpha_g (p_{ig})^{1-\sigma}\right)^{\frac{1}{1-\sigma}}$. 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 that demand shocks are not).

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.

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

From equation (9), 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. If we assume that crop choice is constant within a decade d and each year within a decade is a different state of the world we obtain the following regression formulation of equation (9):

$$\ln p_{igt} = -\sum_{j=1}^{N} T_{ijd} \ln A_{jgt} + \delta_{it} + \delta_{igd} + \delta_{gt} + v_{igt}, \tag{19}$$

where δ_{it} is a location-year fixed effect capturing the weighted aggregate destination demand, δ_{igd} is a location-good-decade fixed effect capturing the weighted destination demand relative to supply, δ_{gt} is a good-year fixed effect capturing the average effect of market tightness on prices, and v_{igt} is a residual capturing the district deviations in the effect of market tightness.[28] While equation (19) follows directly from the structural equation (9), it also has an intuitive interpretation: conditional on the appropriate set of fixed

[28] More precisely, $v_{igt} \equiv \left(\sum_{j=1}^{N} T_{ij}\bar{\varepsilon}_j - \frac{1}{N}\sum_{j=1}^{N}\sum_{k=1}^{N} T_{jk}\bar{\varepsilon}_k\right)\ln \varphi_{gt}$. Note that if all villages shared the same total level of openness (i.e. $\bar{\varepsilon}_i \equiv \sum_{j\neq i}\varepsilon_{ij} = \bar{\varepsilon}$ for all i), then the residual would be equal to zero since $\sum_{j=1}^{N} T_{ij}\bar{\varepsilon}\ln\bar{\varphi}_{gt} = \frac{\bar{\varepsilon}}{\sigma}\ln\bar{\varphi}_{gt}$ would be absorbed by the good-year fixed effect. Hence the residual ε_{igt} captures only deviations of the elasticity weighted average of the total openness of a district's trading partners from the average.

effects, 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.

While the elasticities $\{T_{ijd}\}$ can be estimated non-parametrically if there are a large number of time periods and goods relative to number of locations, unfortunately this is not the case in our empirical context. To proceed, we instead assume that the bilateral Pareto shape parameters are inversely related to travel times:

$$\varepsilon_{ijd} = \beta D_{ijd}^{-\phi}, \tag{20}$$

where we use the same ϕ's and travel time specifications as used in Section 3. Because $\mathbf{E}$ is an M-matrix, we can write its inverse $\mathbf{T}$ as an infinite geometric sum. (see Appendix A.6 for further details). Approximating $\mathbf{T}$ by the first two elements of this series and applying the parametric assumption in equation (20), we can rewrite equation (19) as:

$$\ln p_{igt} = -\gamma_1 \ln A_{igt} - \gamma_2 \sum_{j \neq i} D_{ijd}^{-\phi} \ln \left(\frac{A_{jgt}}{A_{igt}} \right) + \delta_{it} + \delta_{igd} + \delta_{gt} + \mu_{igt}, \tag{21}$$

where $\gamma_1 \equiv \frac{1}{\kappa^2} (2\kappa - \sigma)$, $\gamma_2 \equiv \frac{\beta}{\kappa^2}$ for some $\kappa > 0$ and the residual μ_{igt} captures the higher order terms from the infinite series expansion of $\mathbf{T}$.

Given $D_{ijd}^{-\phi}$, the coefficients γ_1 and γ_2 can be identified using ordinary least squares as long as yields are uncorrelated with the residual (as is the case in our framework where yields are idiosyncratic). Given the previous estimate of σ, these two parameters allow us to recover β and κ and ultimately the bilateral shape parameter ε_{ijd} using equation (20).

Table 5 reports the results of regression (21). As can be seen, prices are lower when both own yields and the distance-weighted sum of other districts' yields are higher. The γ_1 and γ_2 coefficients are both negative and statistically significant regardless of our choice of ϕ (either $\phi = 1$ or $\phi = 1.5$) or our estimate of the off-highway speed of travel (1/3 or 1/4 of that on the highway). In our preferred specification (column 1), the estimates imply that the average Pareto shape parameter between villages in 1970 was 0.16, rising to 0.25 by 2000, indicating high trade costs across locations.[29]

Estimating risk aversion and costs of cultivation from the observed distribution of yields and allocation decisions

From Section 4.4, 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 effective risk-aversion parameter ρ_i. This implies that any

[29] 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 buying or selling locally remains high.

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, lowering its mean return. This relationship is summarized in the farmer's first order conditions from equation (16), which we re-write here:

$$\mu_g^{z,i} = \rho_i \sum_{h=1}^{G} \theta_{ih} \Sigma_{gh}^{z,i} + \lambda_i. \tag{22}$$

Equation (22) forms the basis of our estimation of both effective risk-aversion 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 ρ_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 two limitations: first, they are the nominal revenues rather than the real returns; second, they are the revenues gross rather than net of costs. To address the first problem, we note that given the distribution of trade costs estimated in the previous subsection, we can use Proposition 1 to transform the mean covariance of the (observed) nominal gross yields into the mean and covariance of real returns.[30] To address the second problem, we assume that each good within a district-decade has an unobserved utility cost κ_{igd} that is constant across states of the world and log additive (so that it enters linearly into the first order conditions). As a result, we can re-write equation (22) solely as a function of observables :

$$\mu_g^{z,id} = \rho_{id} \sum_{h=1}^{G} \theta_{ih}^{d} \Sigma_{gh}^{z,id} + \delta_{id} + \delta_{ig} + \delta_{gd} + \zeta_{igd}, \tag{23}$$

where $\delta_{id} \equiv \lambda_{id}$ is the Lagrange multiplier and the unobserved crop cost κ_{igd} is assumed to be a combination of a district-good fixed effect δ_{ig}, a crop-decade fixed effect δ_{gd}, and an idiosyncratic district-crop-decade term ζ_{igd}. Note that given these estimated crop costs (along with the other estimated structural parameters), the farmer's first order conditions will hold with equality at their observed time allocation. In other words, we calibrate the unobserved crop costs so that farmers in all districts and all decades are producing at the optimal point along the mean-variance frontier.

Under the assumption that the production costs are constant within district-decade (and hence mechanically uncorrelated with the covariance of log real returns), ρ_{id} can be estimated using equation (23) using ordinary least squares. To correct for (classical) mea-

[30]To calculate the mean and variance-covariance matrix of yields, we we aggregate across years within district-decade, implicitly assuming that time allocations are constant within decade. Therefore, in what follows we also construct the time allocation within a district-decade by averaging across years.

surement error bias arising, for example, from the fact that our variance-covariance matrix is itself an estimate, we instrument for the marginal contribution to the log variance of real returns with the marginal contribution to the log variance of rainfall-predicted yields $\sum_{h=1} \hat{\Sigma}^{A,i}_{gh} \theta^{1970}_{ih}$ (where $\hat{\Sigma}^{A,i}$ is the estimated variance-covariance matrix using observed rainfall variation and θ^{1970}_{ih} is the observed crop allocation in the 1970s).

Finally, to account for the fact that the effective risk aversion parameter, ρ_{id}, captures both the inherent risk aversion of farmers and their access to risk-mitigating technologies, we allow ρ_{id} to depend on bank access $bank_{id}$ (measured as rural banks per capita):

$$\rho_{id} = \rho^A bank_{id} + \rho^B,$$

so that equation (23) becomes:

$$\mu^{z,id}_g = \rho^A bank_{id} \times \sum_{h=1}^{G} \theta^d_{ih} \Sigma^{z,id}_{gh} + \rho^B \sum_{h=1}^{G} \theta^d_{ih} \Sigma^{z,id}_{gh} + \delta_{id} + \delta_{ig} + \delta_{gd} + \delta + \nu_{igd}. \tag{24}$$

If insurance improves with bank access, we expect $\rho^A < 0$.

Equation (24) follows directly from the structural equation (22) 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 risk the farmer is willing to accept in order to increase her mean returns, the less risk averse she is (and/or the better access to insurance she has).

Table 6 reports the results from the estimation of the effective risk aversion parameters, ρ_{id}, using regression (24).[31] Column 1 finds that there is a strong positive relationship between the mean real returns and the marginal contribution to the variance of real returns, with an effective risk-aversion parameter of 0.9 on average. This estimate is consistent with previous estimates of risk aversion of Indian farmers (e.g. Rosenzweig and Wolpin (1993) who also finds a parameter around 1). Column 2 shows that districts with greater access to banks had a less positive relationship between the mean real returns and the marginal contribution to the variance of real returns, consistent with bank access improving farmer insurance and leading them to act in a manner that appears less risk averse. Columns 3 and 4 show that the point estimates increase slightly for the IV specification, consistent with measurement error creating a downward bias (with column 4 the preferred estimate we use in the quantification). Reassuringly, the combination of

[31] In some districts, the VDSA records very small numbers for sparsely planted crops. In other districts, no number is recorded. As these differences are likely measurement error, and additive measurement error biases upward the variance of log yields, we exclude from the regression any crops which is allocated less than 0.1 percent of land area in a district-decade; including these crops reduces the magnitude of the estimated coefficients but does not change the qualitative results.

fixed effects and the residual from regression (24)—which we interpret as unobserved crop costs, those that ensure the crop choice observed in the data is the optimal choice in the model—positively correlate with actual crop costs we observe at the state-level for a subset of our sample period; see Table 11 in the appendix for further details.

5.2 Trade, volatility and welfare

We now use our structural estimates to quantify the welfare effects of the expansion of the Indian highway network. To isolate the gains from trade, we hold all structural parameters except openness (i.e. the distribution of productivities, crop costs, levels of insurance, and bank access) constant at the estimated level for the 1970s. We then calculate the equilibrium crop choice, the distribution of real returns and the resulting welfare under the estimated distribution of bilateral trade costs in the 1980s, 1990s, and 2000s.[32] Because our parameterization in equation 20 ensures that the estimated bilateral trade costs change over time only through travel time reductions resulting from highway expansions, this procedure isolates the welfare effects of changes to the Indian highway network.

For each district in each decade, we calculate the (log of the arithmetic) mean real returns, the variance of the (log) real returns, and overall welfare (which, after the appropriate monotonic transformation, is a linear combination of the two; see equation (14)). We also decompose the effects of trade into the effects on the production side (the mean and variance farmer nominal income, and the implied welfare of a "producer" who uses this nominal income to purchase a hypothetical numeraire good) and on the consumption side (the mean and variance of the inverse of the price index, and the implied welfare of a "consumer" who uses the income from a sale of a hypothetical numeraire good to purchase the CES consumption bundle).

Table 7 summarizes the changes in theseobjects across decades by projecting the object of interest (e.g. the log of the mean real returns) on a set of decade dummies effect and using district fixed effects so that the dummies report the average change across districts in the object of interest over time. To highlight the effect of the endogenous crop choice of farmers, Panel A first considers the effects of the highway expansion holding farmer crop choice fixed at the observed 1970s allocations. Consistent with the reduced form results of Table 1, we find that the expansion of the highway network increases both the mean and variance of nominal income, increases the mean of the price index (i.e. reduces the mean returns of a "consumer"), and increases the mean and variance of real returns. Given

[32]Because the model implies that all crops will be grown in all villages, for crops that were not grown in a district in a given decade, we set the mean and standard deviation of log yields equal to zero and the area allocated to their production to a small number (1e-6). This effectively implies that any crops that are not grown in the data will not be grown in the counterfactuals (see Figure 4); alternative choices of the small number have a negligible effect on the quantitative results that follow.

our risk aversion estimates (holding bank access at 1970s levels), highway expansions between the 1970s and 2000s increase welfare by approximately 2.5 percent; however, given that the mean real returns increase by 2.9 percent, the increased volatility erodes the first moment gains from trade by approximately 15 percent.

Panel B of Table 7 reports the results allowing farmers to optimally reallocate their production. When farmers choose their crops optimally, the effects of highway expansion are qualitatively similar to Panel A—the mean and variance of nominal income increase, along with the mean of the price index. However, compared to Panel A, when farmers optimally choose their crops, the mean nominal income increases by more and the volatility of nominal income increases by less—as we found in the reduced form results of Table 1. As a result, the expansion of the Indian highways from the 1970s to the 2000s increases the mean real returns of farmers by 3.4 percent without increasing the volatility of real returns, i.e. farmers are able to fully hedge against the increased risk of the highway expansion by altering their crop choice. All told, the highway expansion increases farmer welfare by 3.4 percent—40 percent more than the gains in Panel A, highlighting the importance of accounting for the fact that farmers respond to changes in the risk profile they face by altering their crop choices.[33]

The average gains from trade mask substantial heterogeneity across space. Table 8 explores this heterogeneity. Column 1 of 8 replicates Column 9 of Panel B of Table 7. Column 2 shows that much of the gains from trade over time can be captured by observed improvements in market access, suggesting that the general equilibrium spillovers to other districts are reasonably small (e.g. the coefficient on the 2000s decade dummy falls by three quarters after controlling for observed market access). Figure 3 confirms that districts with greatest increase in market access between the 1970s and the 2000s also tended to have larger gains from trade over the period (the correlation between the two figures is 0.21).

However, Column 3 of Table 8, demonstrates that the welfare gains associated with improvements in market access differed across districts for at least two reasons. First, districts that were initially growing fewer crops had larger gains from improvements to market access, as reductions in trade costs allowed these districts to more easily import crops that were costly to grow locally. Second, (and more interestingly), districts in which

[33]While quantitatively similar, the structural results are substantially smaller in magnitude than the reduced form estimates from Table 1. For example, the reduced form estimates imply that the improvement in market access for the median district between the 1970s and 2000s would be associated with a roughly 37 percent increase in nominal income and a 30 percent increase in real income, whereas the structural estimates find an increase in 2.4 percent and 3.4 percent, respectively. This is consistent with the market access measure being correlated with, amongst other things, improvements in production technology and access to insurance (both of which are held constant in the structural estimation).

the high average yields crops were less risky goods (i.e. the correlation across crops of the mean and standard deviation of log yields was negative) gained more from improvements in market access than districts for which the high average yield crops were also the more risky crops (i.e. the correlation across crops of the mean and standard deviation of log yields was positive). As discussed in Proposition 3, this is because volatility can attenuate the gains from trade when farmers choose not to specialize in goods they are more productive in to avoid incurring additional risk.

To see what this means in terms of how the optimal crop choice responds to the expansion of the highway network, Figure 4 compares the observed mean and standard deviation of log yields in the 1970s (Panels A and B, respectively) to the model's predicted change in the optimal allocation of labor as a result of the highway expansion (Panel C). While the highway expansion does increase the overall labor allocation to cash crops like cotton, it also causes redistribution across space in production, with Northeast India increasing production of wheat, and the South increasing production of sorghum. Consistent with the model prediction that reductions in trade costs lead districts to specialize in their risk-adjusted comparative advantage crops, Panels A and B show that wheat has high mean/low volatility yields in Northeast India, whereas the same is true for sorghum in the South.[34]

All told, the structural estimates demonstrate that, while the expansion of the Indian highway network did increase the risk faced by farmers through the second moment effects of trade, farmers were able to mitigate the welfare loss from this increased risk by altering their planting decisions.

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 lead farmers to reallocate their land toward crops with higher mean yields and lower yield volatility. We then present a novel Ricardian trade model that incorporates a portfolio allocation decision drawn from the finance literature. Risk averse producers choose their optimal allocation of resources across goods and the general equilibrium distribution of real returns is determined by this allocation along with thedistribution of bilateral trade costs and yields. The model yields tractable equations governing equilibrium prices and farmers' resource allocations and generates

[34]Table 12 in the Appendix shows that the model-predicted changes in optimal crop choice from the 1970s are positively correlated with the mean log yields and negatively correlated with the standard deviation of log yields.

the patterns documented in the data.

The model provides intuitive and transparent estimating equations to 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 would have increased the volatility faced by farmers at their current allocations, farmers are able to hedge this risk by changing what they produce, amplifying the gains from trade.

References

ALLEN, T. (2014): "Information frictions in trade," *Econometrica*, 82(6), 2041–2083.

ALLEN, T., AND C. ARKOLAKIS (2014): "Trade and the topography of the spatial economy," *The Quarterly Journal of Economics*.

ASTURIAS, J., M. GARCÍA-SANTANA, AND R. RAMOS (2014): "Competition and the welfare gains from transportation infrastructure: Evidence from the Golden Quadrilateral of India," Discussion paper, Working paper.

ATKIN, D. (2013): "Trade, Tastes, and Nutrition in India," *American Economic Review*, 103(5), 1629–63.

ATKIN, D., AND D. DONALDSON (2015): "Who's Getting Globalized? The Size and Implications of Intra-national Trade Costs," Working Paper 21439, National Bureau of Economic Research.

BASU, P. (2006): *Improving Access to Finance for India's Rural Poor*. World Bank Publications.

BURGESS, R., AND D. DONALDSON (2010): "Can openness mitigate the effects of weather shocks? Evidence from India's famine era," *The American Economic Review*, pp. 449–453.

——— (2012): "Can openness to trade reduce income volatility? Evidence from colonial India's famine era," Discussion paper.

BURGESS, R., AND R. PANDE (2005): "Do Rural Banks Matter? Evidence from the Indian Social Banking Experiment," *American Economic Review*, pp. 780–795.

CAMPBELL, J. Y., AND L. M. VICEIRA (2002): *Strategic asset allocation: portfolio choice for long-term investors*. Oxford University Press.

CASELLI, F., M. KOREN, M. LISICKY, AND S. TENREYRO (2014): "Diversification through trade," Discussion paper.

COSTINOT, A., AND D. DONALDSON (2011): "How Large Are the Gains from Economic Integration? Theory and Evidence from US Agriculture, 1880-2002," *Massachusetts Institute of Technology. Mimeo*.

COSTINOT, A., D. DONALDSON, AND I. KOMUNJER (2011): "What goods do countries trade? A quantitative exploration of Ricardo's ideas," *The Review of Economic Studies*, p. rdr033.

COSTINOT, A., D. DONALDSON, AND C. B. SMITH (2014): "Evolving comparative advantage and the impact of climate change in agricultural markets: Evidence from

1.7 million fields around the world," Discussion paper, National Bureau of Economic Research.

COSTINOT, A., AND A. RODRIGUEZ-CLARE (2013): "Trade theory with numbers: Quantifying the consequences of globalization," Discussion paper, National Bureau of Economic Research.

DATTA, S. (2012): "The impact of improved highways on Indian firms," *Journal of Development Economics*, 99(1), 46–57.

DI GIOVANNI, J., AND A. A. LEVCHENKO (2009): "Trade openness and volatility," *The Review of Economics and Statistics*, 91(3), 558–585.

DISDIER, A.-C., AND K. HEAD (2008): "The puzzling persistence of the distance effect on bilateral trade," *The Review of Economics and statistics*, 90(1), 37–48.

DIXIT, A. (1987): "Trade and insurance with moral hazard," *Journal of International Economics*, 23(3), 201–220.

——— (1989a): "Trade and insurance with adverse selection," *The Review of Economic Studies*, 56(2), 235–247.

——— (1989b): "Trade and insurance with imperfectly observed outcomes," *The Quarterly Journal of Economics*, pp. 195–203.

DIXIT, A., AND V. NORMAN (1980): *Theory of international trade: A dual, general equilibrium approach*. Cambridge University Press.

DONALDSON, D. (2008): "Railroads of the Raj: Estimating the impact of transportation infrastructure," Working paper.

DONALDSON, D., AND R. HORNBECK (2013): "Railroads and American Economic Growth: A" Market Access" Approach," Discussion paper, National Bureau of Economic Research.

EASTERLY, W., R. ISLAM, AND J. E. STIGLITZ (2001): "Shaken and stirred: explaining growth volatility," in *Annual World Bank conference on development economics*, vol. 191, p. 211.

EATON, J., AND G. M. GROSSMAN (1985): "Tariffs as Insurance: Optimal Commercial Policy When Domestic Markets Are Incomplete," *The Canadian Journal of Economics / Revue canadienne d'Economique*, 18(2), pp. 258–272.

EATON, J., AND S. KORTUM (2002): "Technology, geography, and trade," *Econometrica*, 70(5), 1741–1779.

FAFCHAMPS, M. (1992): "Cash crop production, food price volatility, and rural market integration in the third world," *American Journal of Agricultural Economics*, 74(1), 90–99.

FULFORD, S. L. (2013): "The effects of financial development in the short and long run: Theory and evidence from India," *Journal of Development Economics*, 104(0), 56 – 72.

GHANI, E., A. G. GOSWAMI, AND W. R. KERR (2014): "Highway to success: The impact of the Golden Quadrilateral project for the location and performance of Indian manufacturing," *The Economic Journal*.

HEAD, K., AND T. MAYER (2014): "Gravity Equations: Workhorse, Toolkit, and Cookbook," in *Handbook of International Economics*, vol. 4, pp. 131–195. Elsevier.

HELPMAN, E., AND A. RAZIN (1978): *A Theory of International Trade Under Uncertainty*. Academic Press.

JAYACHANDRAN, S. (2006): "Selling labor low: Wage responses to productivity shocks in developing countries," *Journal of political Economy*, 114(3), 538–575.

KARABAY, B., AND J. MCLAREN (2010): "Trade, offshoring, and the invisible handshake," *Journal of international Economics*, 82(1), 26–34.

KUROSAKI, T., AND M. FAFCHAMPS (2002): "Insurance market efficiency and crop choices in Pakistan," *Journal of Development Economics*, 67(2), 419–453.

LEE, H. (2013): "Industrial output fluctuations in developing countries: General equilibrium consequences of agricultural productivity shocks," *Department of Economics, Purdue University, West Lafayette*.

MAHUL, O., N. VERMA, AND D. CLARKE (2012): "Improving farmers' access to agricultural insurance in India," *World Bank Policy Research Working Paper*, (5987).

MUKESH ESWARAN, A. K. (1990): "Implications of Credit Constraints for Risk Behaviour in Less Developed Economies," *Oxford Economic Papers*, 42(2), 473–482.

MUNSHI, K. (2004): "Social learning in a heterogeneous population: technology diffusion in the Indian Green Revolution," *Journal of development Economics*, 73(1), 185–213.

NEWBERY, D., AND J. STIGLITZ (1984): "Pareto inferior trade," *The Review of Economic Studies*, 51(1), 1–12.

PLEMMONS, R. J. (1977): "M-matrix characterizations. I—nonsingular M-matrices," *Linear Algebra and its Applications*, 18(2), 175–188.

ROSENZWEIG, M. R., AND H. P. BINSWANGER (1993): "Wealth, weather risk and the composition and profitability of agricultural investments," *The Economic Journal*, pp. 56–78.

ROSENZWEIG, M. R., AND K. I. WOLPIN (1993): "Credit market constraints, consumption smoothing, and the accumulation of durable production assets in low-income countries: Investments in bullocks in India," *Journal of political economy*, pp. 223–244.

SCOTT, P. T., ET AL. (2013): "Dynamic discrete choice estimation of agricultural land use," *V Tolouse School of Economics*.

SETHIAN, J. (1999): *Level Set Methods and Fast Marching Methods: Evolving Interfaces in Computational Geometry, Fluid Mechanics, Computer Vision, and Materials Science*, vol. 3. Cambridge University Press.

SOTELO, S. (2013): "Trade frictions and agricultural productivity: Theory and evidence from Peru," *Unpublished manuscript, University of Chicago*.

TOWNSEND, R. M. (1994): "Risk and insurance in village India," *Econometrica: Journal of the Econometric Society*, pp. 539–591.

WILLMOTT, C., AND K. MATSUURA (2012): "Terrestrial Precipitation: 1900-2010 Gridded Monthly Time Series, Version 3.02," Discussion paper, University of Delaware, `http://climate.geog.udel.edu/climate/`.

Table 1: REAL INCOME AND ROADS

Dependent variable:	Components of Real Income (Logged)					
	(1)	(2)	(3)	(4)	(5)	(6)
	Mean Nominal Y	Var Nominal Y	Mean P Index	Var P Index	Mean Real Y	Var Real Y
Market Access	0.549***	0.755***	0.086***	0.035	0.451***	0.211
	(0.084)	(0.220)	(0.016)	(0.154)	(0.086)	(0.219)
Market Access (phi=1)	0.387***	0.590***	0.058***	-0.059	0.320***	0.237*
	(0.049)	(0.129)	(0.009)	(0.091)	(0.050)	(0.129)
Market Access (alt. speed)	0.536***	0.720***	0.083***	0.035	0.440***	0.186
	(0.087)	(0.229)	(0.016)	(0.160)	(0.089)	(0.228)
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Decade FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1208	1208	1208	1208	1208	1208

Dependent variable:	Components of Real Income (Logged, 1970s Crop Allocations)					
	(7)	(8)	(9)	(10)	(11)	(12)
	Mean Nominal Y	Var Nominal Y	Mean P Index	Var P Index	Mean Real Y	Var Real Y
Market Access	0.481***	0.888***	0.086***	0.035	0.383***	0.303
	(0.076)	(0.212)	(0.016)	(0.154)	(0.078)	(0.213)
Market Access (phi=1)	0.336***	0.579***	0.058***	-0.059	0.269***	0.214*
	(0.044)	(0.125)	(0.009)	(0.091)	(0.046)	(0.126)
Market Access (alt. speed)	0.466***	0.821***	0.083***	0.035	0.370***	0.254
	(0.079)	(0.220)	(0.016)	(0.160)	(0.082)	(0.221)
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Decade FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1208	1208	1208	1208	1208	1208

Notes: Each entry corresponds to the coefficient on market access from a separate regression of a component of the mean and variance of real income regressed on alternative measures of market access. All regressions also include district and decade fixed effects. Nominal income is calculated as agricultural revenue per hectare over the 15 sample crops. In Panel A, actual crop allocations, prices and yields are used for this calculation, In Panel B, actual yields and prices are used along with the average crop allocations in the 1970s. Price index is a CES price index of the same 15 crops using the CES parameters shown in Table 4. Each observation in each regression is at the district-decade level. Coefficients multiplied by 100,000 for readability. Stars indicate statistical significance: * p<.10 ** p<.05 *** p<.01.

Table 2: PRICE PRODUCTION ELASTICITIES AND ROADS

Dependent variable:	Elasticity of Price to Production				
	(1)	(2)	(3)	(4)	(5)
	IV	IV	OLS	IV	IV
Market Access	0.039***	0.033**	0.025***		
	(0.007)	(0.013)	(0.009)		
Market Access (phi=1)				0.017**	
				(0.008)	
Market Access (alt. speed)					0.034**
					(0.014)
Crop-district FE	Yes	Yes	Yes	Yes	Yes
Crop-decade FE	No	Yes	Yes	Yes	Yes
R-squared	0.339	0.359	0.356	0.359	0.359
Observations	14023	14023	13706	14023	14023
Mean Predicted Value 1970s	-0.043	-0.040	-0.027	-0.040	-0.040
Mean Predicted Value 1980s	-0.038	-0.042	-0.025	-0.042	-0.042
Mean Predicted Value 1990s	-0.029	-0.023	-0.023	-0.024	-0.024
Mean Predicted Value 2000s	-0.022	-0.021	-0.015	-0.021	-0.021

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

Dependent variable:	Fraction of land planted by crop						
	(1)	(2)	(3)	(4) phi=1	(5) phi=1	(6) alt. speed	(7) alt. speed
Log(Mean Yield)	0.004***	-0.010***	-0.013***	-0.025***	-0.026***	-0.008***	-0.012***
	(0.001)	(0.002)	(0.003)	(0.003)	(0.004)	(0.002)	(0.003)
Log(Variance Yield)	-0.001**	0.000	0.001*	0.001*	0.002***	0.000	0.001*
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Log(Mean)XMA		0.019***	0.024***	0.011***	0.012***	0.019***	0.024***
		(0.003)	(0.003)	(0.001)	(0.001)	(0.003)	(0.003)
Log(Var)XMA		-0.001***	-0.002***	-0.001***	-0.001***	-0.001**	-0.002***
		(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
Log(Mean)XBank			0.489*		-0.015		0.575**
			(0.287)		(0.373)		(0.244)
Log(Var)XBank			-0.083		-0.144*		-0.099*
			(0.057)		(0.077)		(0.060)
Log(Mean)XMAXBank			-0.638**		-0.078		-0.733***
			(0.288)		(0.126)		(0.264)
Log(Var)XMAXBank			0.130**		0.063***		0.165***
			(0.052)		(0.024)		(0.058)
Crop-decade FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District-decade FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Crop-district FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.974	0.974	0.974	0.974	0.974	0.974	0.974
Observations	13791	13791	13766	13791	13762	13791	13768

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

Dependent variable:	Log Budget Share	
	(1)	(2)
Transformed Coefficients	OLS	IV
Elasticity σ	1.598***	2.382***
	(0.022)	(0.040)
Rice α	0.110***	0.115***
	(0.001)	(0.001)
Wheat α	0.506***	0.396***
	(0.010)	(0.009)
Sorghum α	0.516***	0.312***
	(0.015)	(0.011)
Pearl Millet α	0.429***	0.311***
	(0.015)	(0.012)
Maize α	0.288***	0.201***
	(0.011)	(0.008)
Barley α	0.199***	0.160***
	(0.021)	(0.015)
Finger Millet α	0.323***	0.205***
	(0.013)	(0.009)
Chickpea α	0.132***	0.195***
	(0.003)	(0.005)
Pigeon Pea α	0.419***	0.974
	(0.012)	(0.046)
Rapeseed α	0.634***	1.433***
	(0.018)	(0.065)
Groundnut α	0.766***	1.661***
	(0.021)	(0.073)
Other Oil α	0.288***	0.417***
	(0.006)	(0.011)
Sugarcane α	0.263***	0.322***
	(0.005)	(0.007)
Other α	5.355***	5.105***
	(0.078)	(0.074)
Village FE	Yes	Yes
First Stage F Stat		6871.21
R-squared	0.69	0.93
Observations	750115	750074

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 5: PRICES, OWN YIELDS AND DISTANCE-WEIGHTED OTHERS' YIELDS

Dependent variable:	Log Price		
	(1)	(2)	(3)
$\ln y_{igt}$	-0.041***	-0.044***	-0.037***
	(0.004)	(0.006)	(0.004)
$\sum_{j \neq i} D_{ij}^{-\phi} \ln(\frac{y_{jgt}}{y_{igt}})$	-0.008***		
	(0.002)		
$\sum_{j \neq i} D_{ij}^{-\phi} \ln(\frac{y_{jgt}}{y_{igt}})$ (phi=1)		-0.002***	
		(0.001)	
$\sum_{j \neq i} D_{ij}^{-\phi} \ln(\frac{y_{jgt}}{y_{igt}})$ (alt. speed)			-0.007***
			(0.002)
District-year FE	Yes	Yes	Yes
Crop-district-decade FE	Yes	Yes	Yes
Crop-year FE	Yes	Yes	Yes
R-squared	0.948	0.948	0.948
Observations	82744	82744	82744

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

	(1) OLS	(2) OLS	(3) IV	(4) IV
Variance of real returns	0.899***	1.349***	1.329***	1.794***
	(0.098)	(0.124)	(0.157)	(0.216)
Rural banks per capita * Variance of real returns		-7.117***		-7.184***
		(1.105)		(2.212)
District-decade FE	Yes	Yes	Yes	Yes
District-crop FE	Yes	Yes	Yes	Yes
Crop-decade FE	Yes	Yes	Yes	Yes
First stage F-stat			964.661	352.048
R-squared	0.860	0.862	0.858	0.860
Observations	11630	11630	11630	11630

Notes: Ordinary least squares. Each observation is a crop-district-decade triplet to which a farmer allocated more than a tenth of a percent of her time. The dependent variable is the mean real returns of a crop. The independent variable is the marginal contribution of a crop to the total variance of real returns. Standard errors clustered at the district-decade level are reported in parentheses. Stars indicate statistical significance: * p<.10 ** p<.05 *** p<.01.

Table 7: WELFARE GAINS FROM EXPANSION OF INDIAN HIGHWAY NETWORK

PANEL A: Crop choice fixed at 1970s levels

	Producers			Consumers			Total		
	(1) Mean	(2) Variance	(3) Welfare	(4) Mean	(5) Variance	(6) Welfare	(7) Mean	(8) Variance	(9) Welfare
1980s	0.008***	0.009***	0.001**	-0.002***	-0.002***	-0.000***	0.006***	0.000**	0.006***
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
1990s	0.017***	0.020***	0.002***	-0.004***	-0.005***	-0.000***	0.015***	0.001***	0.013***
	(0.001)	(0.002)	(0.000)	(0.001)	(0.001)	(0.000)	(0.002)	(0.000)	(0.002)
2000s	0.030***	0.035***	0.004***	-0.006***	-0.006***	-0.000***	0.029***	0.003***	0.025***
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.000)	(0.003)	(0.001)	(0.002)
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	1.000	1.000	1.000	0.978	0.978	0.869	1.000	1.000	1.000
Observations	1232	1232	1232	1232	1232	1232	1232	1232	1232

PANEL B: Optimal crop choice

	Producers			Consumers			Total		
	(1) Mean	(2) Variance	(3) Welfare	(4) Mean	(5) Variance	(6) Welfare	(7) Mean	(8) Variance	(9) Welfare
1980s	0.026***	0.001***	0.024***	-0.011***	0.000***	-0.012***	0.007***	0.000	0.007***
	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
1990s	0.075***	0.001***	0.073***	-0.047***	0.000***	-0.047***	0.018***	-0.000	0.018***
	(0.002)	(0.000)	(0.002)	(0.001)	(0.000)	(0.001)	(0.002)	(0.000)	(0.002)
2000s	0.242***	0.001***	0.240***	-0.191***	0.000*	-0.191***	0.034***	-0.000	0.034***
	(0.006)	(0.000)	(0.006)	(0.002)	(0.000)	(0.002)	(0.002)	(0.000)	(0.002)
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	1.000	1.000	1.000	0.984	0.911	0.984	1.000	1.000	1.000
Observations	1232	1232	1232	1232	1232	1232	1232	1232	1232

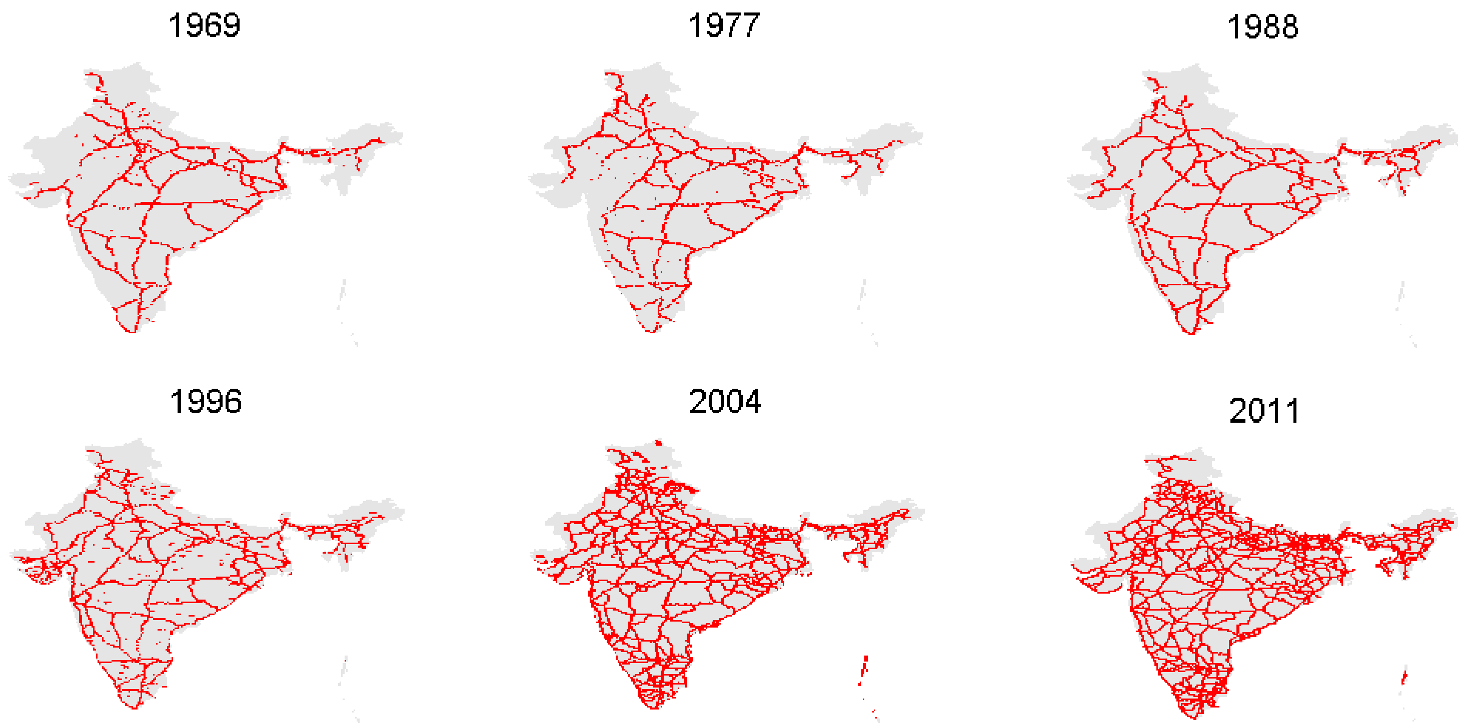
Notes: Ordinary least squares. Each observation is a district-decade pair. The mean column reports the log of the mean returns; the variance column reports the variance of the log returns; and the welfare column uses the estimated risk aversion coefficients to combines the two to create the expected welfare. Columns 1-3 correspond to the norminal income and can be interpreted of the welfare of a producer who uses the nominal income to purchase a numeraire good; Columns 4-6 correspond to the price index and can be interpreted of the welfare of a consumer who uses a constant income to purchase a CES bundle of crops; Columns 7-9 correspond to the agents in the model who earn a nominal income and use it to purchase a CES bundle of crops. Note that because the means are the mean of the log real returns (as opposed to the log of the mean returns), columns (1) and (4) do not necessarily sum to column (7). Standard errors clustered at the district level are reported in parentheses. Stars indicate statistical significance: * p<.10 ** p<.05 *** p<.01.

Table 8: EXPLAINING THE HETEROGENEITY ACROSS DISTRICTS IN THE GAINS FROM THE EXPANSION OF THE INDIAN HIGHWAY NETWORK

	(1)	(2)	(3)
1980s	0.007***	0.000	0.001
	(0.001)	(0.001)	(0.001)
1990s	0.018***	-0.002	0.001
	(0.001)	(0.003)	(0.002)
2000s	0.034***	0.008*	0.012***
	(0.002)	(0.005)	(0.003)
Log market access		0.040***	0.244***
		(0.008)	(0.017)
Number of crops			-0.017***
$\times$ Log market access			(0.001)
Correlation of mean			-0.023**
and std.dev. of yields $\times$ Log MA			(0.009)
District FE	Yes	Yes	Yes
R-squared	1.000	1.000	1.000
Observations	1232	1232	1232

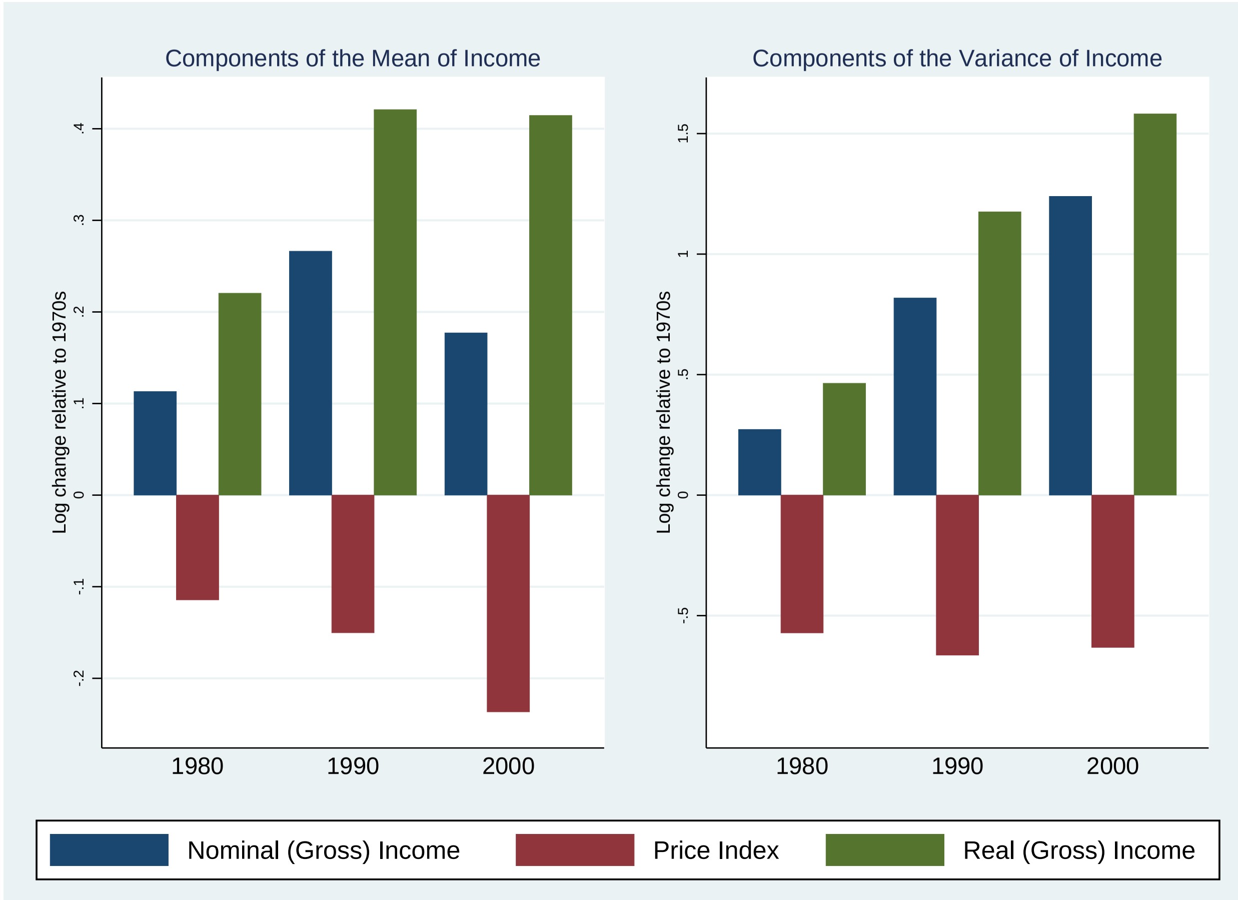
Notes: Ordinary least squares. Each observation is a district-decade pair. The dependent variable is estimated welfare in a district-decade from expanding the Indian highway network (holding all other structural parameters fixed). Number of crops is the number of crops with observed yields in the 1970s in a district. The correlation between mean and standard deviation of yields is the correlation across crops within district; a positive (negative) value indicates that crops with higher means in a district also tend to be more (less) risky. Standard errors clustered at the district level are reported in parentheses. Stars indicate statistical significance: * p<.10 ** p<.05 *** p<.01.

Figure 1: Indian Highway Network over Time



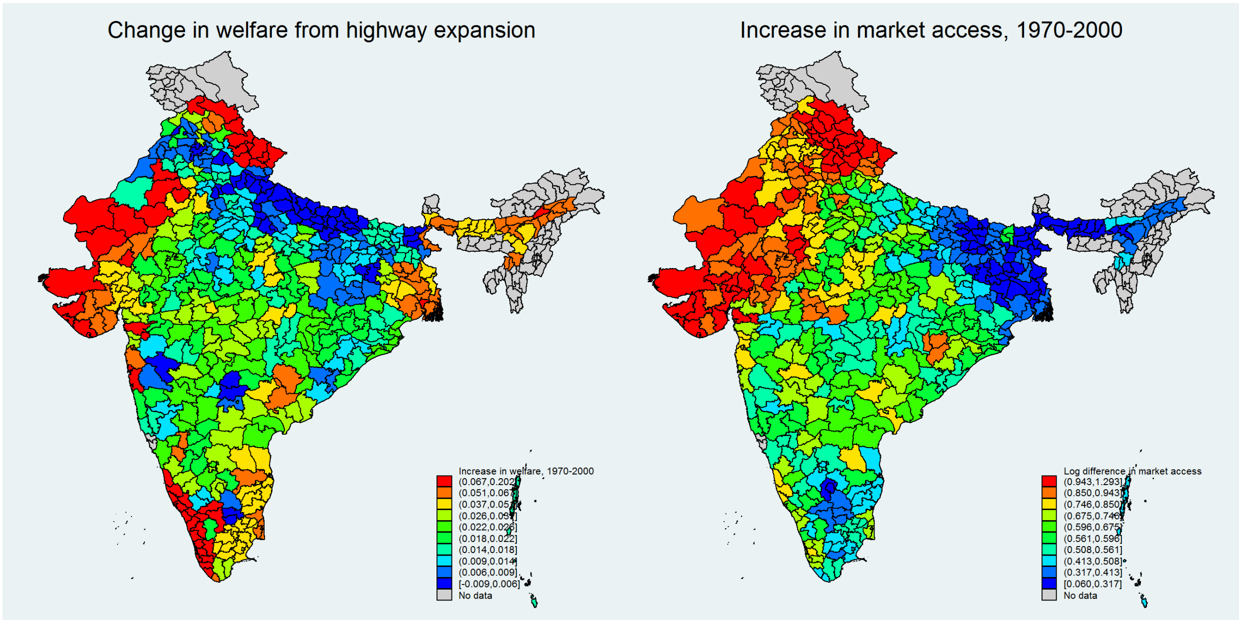
Notes: This figure shows the expansion of the Indian highway network over time. The networks are constructed by geocoding scanned road atlases for each of the above years and using image processing to identify the pixels associated with highways. Bilateral distances between all districts are then calculated by applying the "Fast Marching Method algorithm (see Sethian (1999)) to the resulting speed image.

Figure 2: Decomposition of Income Volatility over Time



Notes: This figure shows how the volatility of real (gross) agricultural incomes and its components have changed over time. The blue bar reports the log change in the volatility in total nominal agricultural revenue relative to the 1970s using observed crop-year-district prices, yields, and crop shares. The red bar reports the log change in the price index, a CES price index for the 15 crops in our sample. The green bar reports the log change in real (gross—i.e. excluding crop costs) income. Each of the values reported are the mean value across districts within a decade.

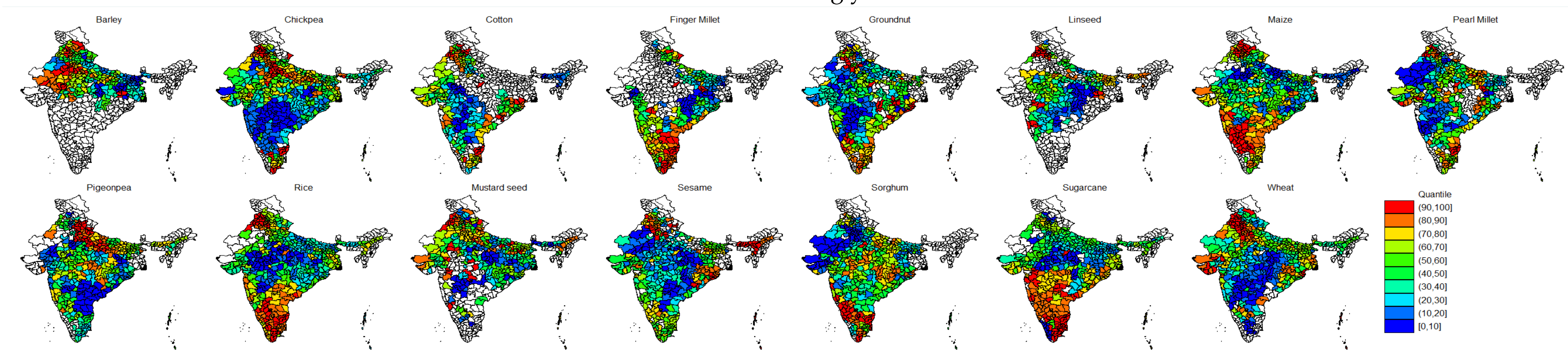
Figure 3: The spatial distribution of the gains from trade



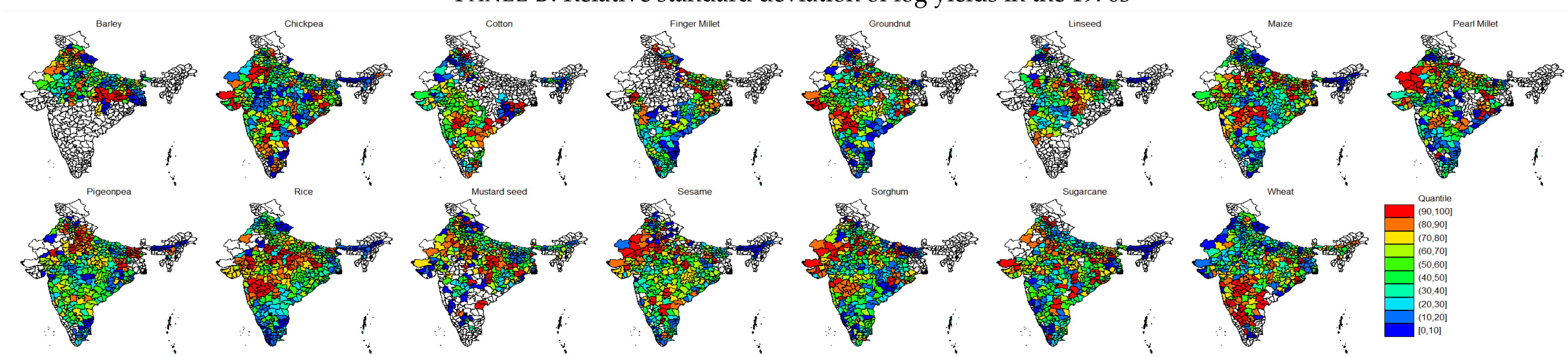
Notes: The left panel figure shows the distribution across districts in the gains from trade from the expansion of the highway network between the 1970s to the 2000s. To calculate the gains from trade, we hold technology and effective risk aversion parameters constant at their 1970s levels but allow trade costs to change as the Indian highway network expands over time. For each district in each decade, we then calculate the optimal reallocation of labor across different crops and the associated change welfare. The right frame shows the spatial dispersion of change in market access between the 1970s and the 2000s, where the market access is measured as an inverse travel time weighted average of agricultural output in all districts, and travel times are calculated using the observed highway network. In both figures, the gains are reported by decile, where red indicates greater gains and blue indicates smaller gains.

Figure 4: Crop characteristics and the response of crop allocations to the Indian Highway Expansion

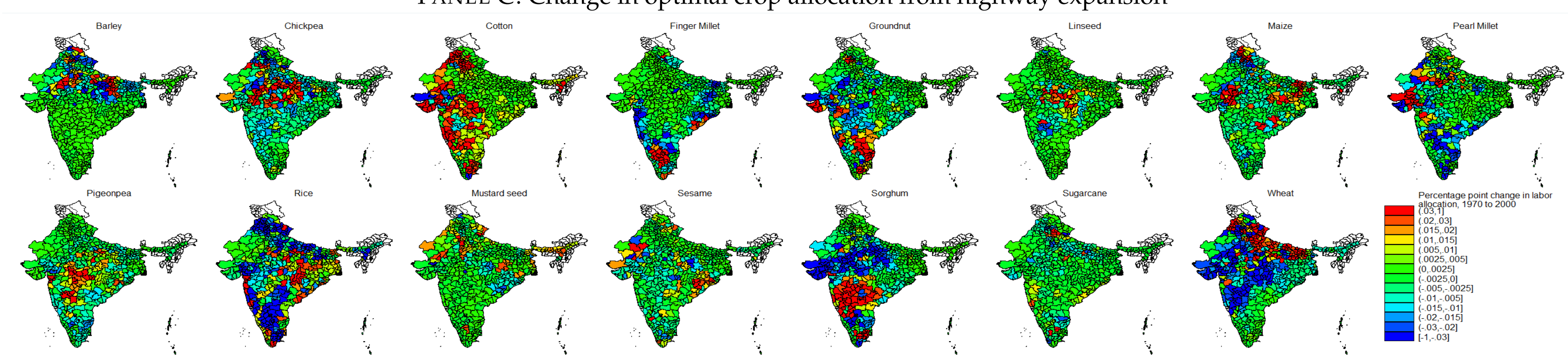
PANEL A: Relative mean log yields in the 1970s



PANEL B: Relative standard deviation of log yields in the 1970s



PANEL C: Change in optimal crop allocation from highway expansion



Notes: Panels A and B report the decile of average log yields and standard deviation of log yields of each crop in each district in the 1970s, respectively. Panel C reports the percentage point change in labor allocated to the production of each crop in each district in response to the expansion of the Indian highway network.

A Appendix

A.1 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 of state of the world s with π_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:

$$C_s = \kappa I_s^{\chi} E\left(I_s\right)^{1-\chi}, \tag{25}$$

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

To micro-found equation (25), 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:

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

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:

$$\sum_{t\neq s} \pi_t \frac{1}{1-\lambda}\left(I_t + \varepsilon p_s\right)^{1-\lambda} + \pi_s \frac{1}{1-\lambda}\left(I_t + \varepsilon p_s - \varepsilon\right)^{1-\lambda} = \sum_t \pi_t \frac{1}{1-\lambda} I_t^{1-\lambda},$$

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

$$p_{s}\varepsilon\sum_{t\neq s}\pi_{t}I_{t}^{-\lambda}=\varepsilon\left(1-p_{s}\right)\pi_{s}I_{s}^{-\lambda}\iff$$
$$p_{s}=\frac{\pi_{s}I_{s}^{-\lambda}}{\sum_{t}\pi_{t}I_{t}^{-\lambda}}. \tag{26}$$

Equation (26) 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:

$$\pi_{s}\left(I_{s}+q_{s}-\sum_{t}p_{t}q_{t}\right)^{-\rho}=p_{s}\sum_{t}\pi_{t}\left(I_{t}+q_{t}-\sum_{t}p_{t}q_{t}\right)^{-\rho}\iff$$
$$\frac{\pi_{s}C_{s}^{-\rho}}{\sum_{t}\pi_{t}C_{t}^{-\rho}}=p_{s}. \tag{27}$$

Substituting the equilibrium price from equation (26) into equation (27) and noting that $E\left[C^{-\rho}\right]=\sum_{t}\pi_{t}C_{t}^{-\rho}$ and $E\left[I^{-\lambda}\right]=\sum_{t}\pi_{t}I_{t}^{-\lambda}$ yields:

$$\frac{C_{s}^{-\rho}}{E\left[C^{-\rho}\right]}=\frac{I_{s}^{-\lambda}}{E\left[I^{-\lambda}\right]}. \tag{28}$$

As in the paper, suppose that $\ln I\sim N\left(\mu_{I},\sigma_{I}^{2}\right)$. Then we have:

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

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

$$\ln\left(\frac{C^{-\rho}}{E\left[C^{-\rho}\right]}\right)\sim N\left(-\frac{1}{2}\lambda^{2}\sigma_{I}^{2},\lambda^{2}\sigma_{I}^{2}\right)\iff$$
$$\ln C\sim N\left(\mu_{C},\frac{\lambda^{2}}{\rho^{2}}\sigma_{I}^{2}\right),$$

where μ_C is an arbitrary mean of log returns. The arbitrary mean arises because the first order conditions (27) 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:

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

As a result, we can re-write equation (28) as:

$$\begin{aligned} C_s &= I_s^{\frac{\lambda}{\rho}} E\left[C^{-\rho}\right]^{-\frac{1}{\rho}} E\left[I^{-\lambda}\right]^{\frac{1}{\rho}} \iff \\ C_s &= \kappa I_s^{\chi} E\left(I_s\right)^{1-\chi}, \end{aligned}$$

where $\chi \equiv \frac{\lambda}{\rho} \in [0,1]$ and $\kappa \equiv \frac{E[I_s]^{\chi}}{E\left[I_s^{\chi}\right]}$ as claimed.

A.2 An alternative derivation of the no-arbitrage equation based on convex transportation costs

In the paper, we show that under the appropriate set of assumptions, heterogeneous traders and a market clearing condition imply the following no-arbitrage condition:

$$\frac{C_{ig}\left(s\right)}{Q_{ig}\left(s\right)} = \prod_{j\neq i}\left(\frac{p_{ig}\left(s\right)}{p_{jg}\left(s\right)}\varphi_g\left(s\right)\right)^{\varepsilon_{ij}},$$

i.e. goods flow toward locations with higher relative prices. In this subsection, we provide an alternative setup that generates the same no-arbitrage condition assuming that transportation costs are increasing and convex in the quantity traded.[35] For notational simplicity, we omit the good g and state s notation in what follows.

Suppose that iceberg trade costs τ_{ij} between i and j are increase in the quantity shipped from i to j with the following functional form:

$$\ln \tau_{ij} = \frac{1}{\varepsilon_{ij}}\left(Q_{ij} + \kappa_i - \kappa_j\right), \tag{29}$$

where $\{\kappa_i\}$ are (endogenous) constants that capture the relative cost of importing versus exporting from a particular location (a larger κ_i indicates it is relatively more costly to export from a location than for that location to import). Because these are relative costs, without loss of generality we assume $\sum_{i=1}^{N}\kappa_i = 0$.

In equilibrium, trade flows from i to j, Q_{ij}, will only be positive if $p_j \geq p_i$, in which case the following no-arbitrage condition holds:

$$\begin{aligned} \ln p_j - \ln p_i &= \ln \tau_{ij} \iff \\ \ln p_j - \ln p_i &= \ln \varphi + \frac{1}{\varepsilon_{ij}}\left(Q_{ij} + \kappa_i - \kappa_j\right) \iff \\ Q_{ij} &= \varepsilon_{ij}\left(\ln p_j - \ln p_i - \ln \varphi\right) - \kappa_i + \kappa_j \end{aligned} \tag{30}$$

[35]We are grateful to Rodrigo Adao for pointing out this alternative setup.

¡Similarly, trade flows from j to i, Q_{ji}, will only be positive if $p_i \geq p_j$, in which case the following no-arbitrage equation holds:

$$\begin{aligned}
\ln p_i - \ln p_j = \ln \tau_{ji} &\iff \\
\ln p_i - \ln p_j = \ln \varphi + \frac{1}{\varepsilon_{ji}} \left(Q_{ji} + \kappa_j - \kappa_i\right) &\iff \\
Q_{ji} = \varepsilon_{ji} \left(\ln p_i - \ln p_j - \ln \varphi\right) + \kappa_i - \kappa_j &
\end{aligned} \tag{31}$$

Market clearing implies the total quantity consumed is equal to the total quantity imported:

$$C_i = Q_{ii} + \sum_{j \neq i} Q_{ji},$$

while the total quantity produced is equal to the total quantity exported:

$$Q_i = Q_{ii} + \sum_{j \neq i} Q_{ij}.$$

Hence the difference between the quantity consumed and the quantity produced is simply equal to the net imports:

$$C_i - Q_i = \sum_{j \neq i} Q_{ji} - \sum_{j \neq i} Q_{ij}. \tag{32}$$

As in the main text, assume that $\varepsilon_{ij} = \varepsilon_{ji}$. Then substituting the no-arbitrage equations (30) and (31) into the market clearing condition (32) yields:

$$\begin{aligned}
C_i - Q_i &= \sum_{Q_{ji} > 0} \left(\varepsilon_{ji} \left(\ln p_i - \ln p_j\right) + \kappa_i - \kappa_j\right) - \sum_{Q_{ij} > 0} \left(\varepsilon_{ij} \left(\ln p_j - \ln p_i\right) - \kappa_i + \kappa_j\right) \iff \\
C_i - Q_i &= \sum_{j \neq i} \varepsilon_{ij} \left(\ln p_i - \ln p_j\right) + \sum_{j \neq i} \left(\kappa_i - \kappa_j\right)
\end{aligned} \tag{33}$$

Finally, we suppose that:

$$\sum_{j \neq i} \left(\kappa_i - \kappa_j\right) = \left(C_i - \ln C_i\right) - \left(Q_i - \ln Q_i\right) + \sum_{j \neq i} \varepsilon_{ij} \ln \varphi, \tag{34}$$

for some $\varphi > 0$. Note that equation (34) can be written in matrix notation as:

$$\mathbf{A}\vec{\kappa} = \mathbf{b},$$

where $\mathbf{A} = \left[A_{ij}\right] = \begin{cases} \sum_{i \neq j} \varepsilon_{ij} & \text{if } i = j \\ -\varepsilon_{ij} & \text{if } i \neq j \end{cases}$ and $\mathbf{b} = \left[\left(C_i - \ln C_i\right) - \left(Q_i - \ln Q_i\right) + \sum_{j \neq i} \varepsilon_{ij} \ln \varphi\right]$. Note that $\mathbf{A}$ has rank $N - 1$, so with the additional constraint that $\sum_{i=1}^{N} \kappa_i = 0$ there is a unique set of $\{\kappa_i\}$ that solve equation (34) . Furthermore, the φ can be determined by the aggregate market clearing constraint that:

$$
\begin{aligned}
\sum_{i=1}^{N}\left(C_i - Q_i\right) = 0 \iff \\
\sum_{i=1}^{N}\left(\sum_{j\neq i}\varepsilon_{ij}\left(\ln p_i - \ln p_j\right) + \sum_{j\neq i}\left(\kappa_i - \kappa_j\right)\right) = 0 \iff \\
\sum_{i=1}^{N}\sum_{j\neq i}\left(\kappa_i - \kappa_j\right) = \sum_{i=1}^{N}\sum_{j\neq i}\varepsilon_{ij}\left(\ln p_j - \ln p_i\right)
\end{aligned}
$$

As a result, equation (33) becomes:

$$
\begin{aligned}
C_i - Q_i &= \sum_{i\neq j}\varepsilon_{ij}\left(\ln p_i - \ln p_j\right) + \sum_{i\neq j}\left(\kappa_i - \kappa_j\right) \iff \\
\ln C_i - \ln Q_i &= \sum_{i\neq j}\varepsilon_{ij}\left(\ln p_i - \ln p_j + \ln \varphi\right) \iff \\
\frac{C_i}{Q_i} &= \prod_{i\neq j}\left(\frac{p_i}{p_j}\varphi\right)^{\varepsilon_{ij}}, \qquad (35)
\end{aligned}
$$

as required.

A.3 Derivation of the equilibrium crop choice

In this subsection, we provide the full derivation of the equilibrium crop choice when yields are both deterministic and volatile.

A.3.1 No volatility

We begin with the fact that the returns per unit hectare of all crops that farmers produce must be equalized for farmers to be willing to produce them. Taking logs of equation (11) yields:

$$\ln p_{ig} + \ln A_{ig} = \ln w_i. \qquad (36)$$

Recall from equation (9) that combining the no-arbitrage equation and the CES demand equation yields the following set of equilibrium prices:

$$\ln p_{ig} = \frac{1}{\sigma}\ln \alpha_g + \sum_{j=1}^{N} T_{ij}\ln D_j - \sum_{j=1}^{N} T_{ij}\ln\left(\varphi_g^{\bar{\varepsilon}_j}\right) - \sum_{j=1}^{N} T_{ij}\ln A_{jg} - \sum_{j=1}^{N} T_{ij}\ln \theta_{jg}. \qquad (37)$$

Note from the previous equation that because $T_{ii} > 0$, as the land allocated to crop g in location i goes to zero, its price rises to infinity, which implies that all crops will be produces in positive amounts in all locations; intuitively, there will always be some "buying" traders with very high trade costs that will choose to source locally regardless of the local price.

Substituting the equilibrium price equation (37) into the farmer indifference condition equation (36) yields:

$$
\begin{aligned}
\frac{1}{\sigma}\ln\alpha_g + \sum_{j=1}^{N} T_{ij}\ln D_j - \sum_{j=1}^{N} T_{ij}\ln\left(\varphi_g^{\bar{\varepsilon}_j}\right) - \sum_{j=1}^{N} T_{ij}\ln A_{jg} - \sum_{j=1}^{N} T_{ij}\ln\theta_{jg} + \ln A_{ig} = \ln w_i \iff \\
\frac{1}{\sigma}\ln\alpha_g + \sum_{j=1}^{N} T_{ij}\ln D_j - \sum_{j=1}^{N} T_{ij}\ln\varphi_g^{\bar{\varepsilon}_j} - \sum_{j=1}^{N} T_{ij}\ln A_{jg} + \ln A_{ig} - \ln w_i = \sum_{j=1}^{N} T_{ij}\ln\theta_{jg} \iff \\
\frac{1}{\sigma}\ln\alpha_g + \mathbf{T}\ln\vec{D} - \mathbf{T}\ln\vec{\varphi_g^{\bar{\varepsilon}}} - \mathbf{T}\ln\vec{A}_g + \ln\vec{A}_g - \ln\vec{w} = \mathbf{T}\ln\vec{\theta}_g,
\end{aligned}
$$

where the last line writes the system of equation in matrix notation. Multiplying both sides of the equation by $\mathbf{T}^{-1} = \mathbf{E}$ allows us to solve for the equilibrium pattern of specialization up to scale:

$$
\begin{aligned}
\ln\vec{\theta}_g &= \mathbf{E}\left(\frac{1}{\sigma}\ln\alpha_g + \ln\vec{A}_g - \ln\vec{w}\right) + \ln\vec{D} - \ln\vec{\varphi_g^{\bar{\varepsilon}}} - \ln\vec{A}_g \iff \\
\ln\theta_{ig} &= \sum_{j=1}^{N} E_{ij}\left(\frac{1}{\sigma}\ln\alpha_g + \ln A_{jg} - \ln w_j\right) + \ln D_i - \ln\varphi_g^{\bar{\varepsilon}_i} - \ln A_{ig} \iff \\
\ln\theta_{ig} &= \left(\sigma + \sum_{j\neq i}\varepsilon_{ij}\right)\left(\frac{1}{\sigma}\ln\alpha_g + \ln A_{ig} - \ln w_i\right) - \sum_{j\neq i}\varepsilon_{ij}\left(\frac{1}{\sigma}\ln\alpha_g + \ln A_{jg} - \ln w_j\right) + \ln D_i - \ln\varphi_g^{\bar{\varepsilon}_i} - \ln A_{ig} \iff \\
\ln\theta_{ig} &= \ln\alpha_g + (\sigma-1)\ln A_{ig} - \ln\varphi_g^{\bar{\varepsilon}_i} + \sum_{j\neq i}\varepsilon_{ij}\left(\ln A_{ig} - \ln A_{jg}\right) + \left(\ln D_i - \sigma\ln w_i - \sum_{j\neq i}\varepsilon_{ij}\left(\ln w_i - \ln w_j\right)\right) \iff \\
\ln\theta_{ig} &= \ln\alpha_g + (\sigma-1)\ln A_{ig} - \ln\varphi_g^{\bar{\varepsilon}_i} + \sum_{j\neq i}\varepsilon_{ij}\left(\ln A_{ig} - \ln A_{jg}\right) + C_i \iff \\
\theta_{ig} &\propto \alpha_g A_{ig}^{\sigma-1}\varphi_g^{-\bar{\varepsilon}_i}\prod_{j\neq i}\left(\frac{A_{ig}}{A_{jg}}\right)^{\varepsilon_{ij}},
\end{aligned}
$$

where $C_i \equiv \ln D_i - \sigma\ln w_i - \sum_{j\neq i}\varepsilon_{ij}\left(\ln w_i - \ln w_j\right)$ is a crop-invariant constant. Finally, imposing the land constraint that $\sum_{g=1}^{G}\theta_{ig} = 1$, we can solve for the scale, yielding:

$$
\theta_{ig} = \frac{\alpha_g A_{ig}^{\sigma-1}\varphi_g^{-\bar{\varepsilon}_i}\prod_{j\neq i}\left(\frac{A_{ig}}{A_{jg}}\right)^{\varepsilon_{ij}}}{\sum_{h=1}^{G}\alpha_h A_{ih}^{\sigma-1}\varphi_h^{-\bar{\varepsilon}_i}\prod_{j\neq i}\left(\frac{A_{ih}}{A_{jh}}\right)^{\varepsilon_{ij}}},
$$

as required.

A.3.2 With volatility

The derivation of the optimal crop choice in the presence of volatility proceeds analogously to the deterministic case, with the first order conditions of the portfolio choice problem in equation (16) replacing the farmer indifference condition from equation (11):

$$
\mu_g^{z,i} - \rho_i\sum_{h=1}^{G}\theta_{ih}\Sigma_{gh}^{z,i} = \lambda_i,
$$

where $\mu_g^{z,i} \equiv \frac{\exp\left\{\mu_g^{x,i}\right\}}{\sum_{g=1}^{G} \theta_{ig} \exp\left\{\mu_g^{x,i}\right\}} + \frac{1}{2}\Sigma_{gg}^{x,i} - \sum_{h=1}^{G} \theta_{ih} \left(\Sigma_{gh}^{x,i} - \Sigma_{gh}^{z,i}\right)$. Note that we can re-write this as:

$$\begin{aligned}
\mu_g^{x,i} &= \ln \left(\lambda_i - \left(\frac{1}{2}\Sigma_{gg}^{x,i} - \sum_{h=1}^{G} \theta_{ih} \left(\Sigma_{gh}^{x,i} - \Sigma_{gh}^{z,i}\right) - \rho_i \sum_{h=1}^{G} \theta_{ih} \Sigma_{gh}^{z,i} \right) \right) \\
&\quad + \ln \sum_{g=1}^{G} \theta_{ig} \exp\left\{\mu_g^{x,i}\right\} \iff \\
\frac{1}{\sigma} \ln \alpha_g - \sum_{j=1}^{N} T_{ij} \ln \bar{\varphi}_g^{\bar{\varepsilon}_j} - \sum_{j=1}^{N} T_{ij} \left(\ln \theta_{jg} + \mu_g^{A,j}\right) + \mu_g^{A,i} &= \ln \left(\lambda_i - \left(\frac{1}{2}\Sigma_{gg}^{x,i} - \sum_{h=1}^{G} \theta_{ih} \left(\Sigma_{gh}^{x,i} - \Sigma_{gh}^{z,i}\right) - \rho_i \sum_{h=1}^{G} \theta_{ih} \Sigma_{gh}^{z,i} \right) \right) \\
&\quad + \ln \sum_{g=1}^{G} \theta_{ig} \exp\left\{\mu_g^{x,i}\right\}
\end{aligned}$$

where the second line substituted in the expression for $\mu_g^{x,i}$ from equation (38) from Proposition 1. Rearranging this expression yields the following system of equations for the equilibrium crop choice:

$$\begin{aligned}
\sum_{j=1}^{N} T_{ij} \ln \theta_{jg} =& \frac{1}{\sigma} \ln \alpha_g - \sum_{j=1}^{N} T_{ij} \ln \bar{\varphi}_g^{\bar{\varepsilon}_j} - \sum_{j=1}^{N} T_{ij} \mu_g^{A,j} + \mu_g^{A,i} \\
& - \ln \left(\lambda_i - \left(\frac{1}{2}\Sigma_{gg}^{x,i} - \sum_{h=1}^{G} \theta_{ih} \left(\Sigma_{gh}^{x,i} - \Sigma_{gh}^{z,i}\right) - \rho_i \sum_{h=1}^{G} \theta_{ih} \Sigma_{gh}^{z,i} \right) \right) - \ln \sum_{g=1}^{G} \theta_{ig} \exp\left\{\mu_g^{x,i}\right\},
\end{aligned}$$

which as in the deterministic case can be inverted to (implicitly) solve for the equilibrium crop choice up to scale:

$$\begin{aligned}
\ln \theta_{ig} =& \sum_{j=1}^{N} E_{ij} \left(\frac{1}{\sigma} \ln \alpha_g \right) - \ln \bar{\varphi}_g^{\bar{\varepsilon}_j} - \mu_g^{A,i} \\
& + \sum_{j=1}^{N} E_{ij} \left(\mu_g^{A,i} - \ln \left(\lambda_i - \left(\frac{1}{2}\Sigma_{gg}^{x,i} - \sum_{h=1}^{G} \theta_{ih} \left(\Sigma_{gh}^{x,i} - \Sigma_{gh}^{z,i}\right) - \rho_i \sum_{h=1}^{G} \theta_{ih} \Sigma_{gh}^{z,i} \right) \right) \right) - C_i \iff \\
\ln \theta_{ig} =& \ln \alpha_g - \ln \bar{\varphi}_g^{\bar{\varepsilon}_j} - \mu_g^{A,i} + \sigma \ln b_{ig} + \sum_{j \neq i} \varepsilon_{ij} \left(\ln b_{ig} - \ln b_{jg}\right) - C_i
\end{aligned}$$

where $C_i \equiv \sum_{j=1}^{N} E_{ij} \ln \sum_{g=1}^{G} \theta_{ig} \exp\left\{\mu_g^{x,i}\right\}$ is a good invariant constant and:

$$\ln b_{ig} \equiv \mu_g^{A,i} - \ln \left(\lambda_i - \left(\frac{1}{2}\Sigma_{gg}^{x,i} - \sum_{h=1}^{G} \theta_{ih} \left(\Sigma_{gh}^{x,i} - \Sigma_{gh}^{z,i}\right) - \rho_i \sum_{h=1}^{G} \theta_{ih} \Sigma_{gh}^{z,i} \right) \right).$$

Taking the exponent of both sides, this yields:

$$\theta_{ig} \propto \alpha_g \exp\left(\mu_g^{A,i}\right)^{-1} \bar{\varphi}_g^{-\bar{\varepsilon}_i} b_{ig}^{\sigma} \prod_{j \neq i} \left(\frac{b_{ig}}{b_{jg}} \right)^{\varepsilon_{ij}},$$

as required.

A.4 Proof of Proposition 1

Proposition. *[Restated with all definitions]The distribution of the real returns of farmer f in location i is approximately log-normal, i.e.:*

$$\ln Z_i^f \sim N\left(\mu_i^Z, \sigma_i^{2,Z}\right),$$

where μ_i^Z and $\sigma_i^{2,Z}$ are defined in Appendix A.4.

Proposition 4. *The mean of the log real returns can be expressed as:*

$$\begin{aligned}
\mu_i^Z \equiv & \ln \sum_{g=1}^{G} \theta_{ig}^f \exp\left\{\mu_g^{x,i}\right\} + \frac{1}{\sigma-1} \ln \sum_{g=1}^{G} \alpha_g \exp\left\{\mu_g^{y,i}\right\} \\
& + \frac{1}{2}\left(\sum_{g=1}^{G} \theta_{ig}^f \Sigma_{gg}^{x,i} - \sum_{g=1}^{G}\sum_{h=1}^{G} \theta_{ih}^f \theta_{ig}^f \Sigma_{gh}^{x,i}\right) \\
& + \frac{1}{2}(\sigma-1)\left(\sum_{g=1}^{G} \alpha_g \Sigma_{gg}^{p,i} - \frac{1}{2}\sum_{g=1}^{G}\sum_{h=1}^{G} \alpha_g \alpha_h \Sigma_{gh}^{p,i}\right) \\
& + \ln\left(1+\bar{\phi}\right),
\end{aligned}$$

where $\mu_g^{x,i}$ is the mean of the log nominal revenue of crop g per unit time:

$$\mu_g^{x,i} \equiv \frac{1}{\sigma} \ln \alpha_g - \left(\sum_{j=1}^{N} T_{ij} \bar{\varepsilon}_j\right)\left(\ln \bar{\varphi}_g\right) - \sum_{j=1}^{N} T_{ij}\left(\ln \theta_{jg} + \mu_g^{A,j}\right) + \mu_g^{A,i}, \tag{38}$$

$\mu_g^{y,i}$ is the mean of the log price of good g (to the power of $(1-\sigma)$):

$$\mu_g^{y,i} \equiv (1-\sigma)\left(\frac{1}{\sigma}\ln \alpha_g - \left(\sum_{j=1}^{N} T_{ij}\bar{\varepsilon}_j\right)\ln \bar{\varphi}_g - \sum_{j=1}^{N} T_{ij}\left(\ln \theta_{jg} + \mu_g^{A,j}\right)\right),$$

$\Sigma^{x,i}$ is the $G \times G$ variance-covariance matrix of nominal revenue across crops:

$$\begin{aligned}
\Sigma^{x,i} = & \left((1-T_{ii})\,\mathbf{I} - \left(\sum_{j=1}^{N} T_{ij}\bar{\varepsilon}_j\right)\mathbf{D}^{\varphi,i}\right)\Sigma^{A,i}\left((1-T_{ii})\,\mathbf{I} - \left(\sum_{j=1}^{N} T_{ij}\bar{\varepsilon}_j\right)\mathbf{D}^{\varphi,i}\right)' \\
& + \sum_{j\neq i}\left(\left(\sum_{j=1}^{N} T_{ij}\bar{\varepsilon}_j\right)\mathbf{D}^{\varphi,j} + T_{ij}\mathbf{I}\right)\Sigma^{A,j}\left(\left(\sum_{j=1}^{N} T_{ij}\bar{\varepsilon}_j\right)\mathbf{D}^{\varphi,j} + T_{ij}\mathbf{I}\right)',
\end{aligned}$$

$\Sigma^{p,i}$ is the $G \times G$ variance-covariance matrix of prices across crops:

$$\Sigma^{p,i} = \sum_{j=1}^{N}\left(\left(\sum_{j=1}^{N} T_{ij}\bar{\varepsilon}_j\right)\mathbf{D}^{\varphi,j} + T_{ij}\mathbf{I}\right)\Sigma^{A,j}\left(\left(\sum_{j=1}^{N} T_{ij}\bar{\varepsilon}_j\right)\mathbf{D}^{\varphi,j} + T_{ij}\mathbf{I}\right)',$$

$\bar{\phi}$ is the return to farmers from traders and $\bar{\varphi}_g$ is the equilibrium market tightness, both evaluated at the mean of the log realized productivity shocks, and $\mathbf{D}^{\varphi,j} \equiv \left[\frac{\partial \ln \varphi_g}{\partial \ln A_{jh}}\right]_{gh}$ is the $G \times G$ matrix of elasticities of the market tightness with respect to productivity shocks in village j, evaluated at the mean of the log realized productivity shocks.

The variance of the log real returns can be expressed as:

$$\sigma_i^{2,Z} = \sum_{g=1}^{G} \sum_{h=1}^{G} \theta_{ig}^{f} \theta_{ih}^{f} \Sigma_{gh}^{z,i},$$

where:

$$\Sigma^{z,i} \equiv \left(\mathbf{I} - \left(T_{ii}\mathbf{B} + \left(\sum_{j=1}^{N} T_{ij}\bar{\varepsilon}_j \right) \mathbf{B}\mathbf{D}^{\varphi,j} + \tilde{\mathbf{D}}^{\phi,i} \right) \right) \Sigma^{A,i} \left(\mathbf{I} - \left(T_{ii}\mathbf{B} + \left(\sum_{j=1}^{N} T_{ij}\bar{\varepsilon}_j \right) \mathbf{B}\mathbf{D}^{\varphi,j} + \tilde{\mathbf{D}}^{\phi,j} \right) \right)'$$
$$+ \sum_{j \neq i} \left(T_{ij}\mathbf{B} + \left(\sum_{k=1}^{N} T_{jk}\bar{\varepsilon}_k \right) \mathbf{B}\mathbf{D}^{\varphi,j} + \tilde{\mathbf{D}}^{\phi,i} \right) \Sigma^{A,j} \left(T_{ij}\mathbf{B} + \left(\sum_{k=1}^{N} T_{jk}\bar{\varepsilon}_k \right) \mathbf{B}\mathbf{D}^{\varphi,j} + \tilde{\mathbf{D}}^{\phi,j} \right)',$$

$\mathbf{B} \equiv (\mathbf{I}_G - \mathbf{1}_G \vec{\alpha}')$ *is a* $G \times G$ *matrix (where* $\mathbf{1}_G$ *is an* $G \times 1$ *matrix of ones and* $\vec{\alpha} \equiv [\alpha_g]_g$*) and* $\tilde{\mathbf{D}}^{\phi,j} \equiv \mathbf{1}_G \left(\mathbf{D}^{\phi,j}\right)'$*, where* $\mathbf{D}^{\phi,j} \equiv \left[\frac{\partial \ln \phi}{\partial \ln A_{jg}}\right]_g$ *is a vector of elasticities of the return to farmers from traders to the productivity shocks in village j.*

Proof. We first log-linearize equilibrium market tightness and transfers from farmers. From equation (10), given the crop choice of farmers, the equilibrium market tightness $\{\varphi_g\}$ and transfers from traders to farmers ϕ can be written as implicit functions of the realized productivity shocks. As a result, we can log-linearize both around the mean of log productivities:

$$\ln \varphi \left(\{\ln A_{ig}(s)\} \right) \approx \ln \bar{\varphi} \left(\left\{ \mu_g^{A,i} \right\} \right) + \sum_{j=1}^{N} \mathbf{D}^{\varphi,j} \left(\ln A_j(s) - \mu^{A,j} \right)$$
$$\ln \left(1 + \phi \left(\{\ln A_{ig}(s)\} \right) \right) \approx \ln \left(1 + \bar{\phi} \left(\left\{ \mu_g^{A,i} \right\} \right) \right) + \sum_{j=1}^{N} \mathbf{D}^{\phi,j} \left(\ln A_j(s) - \mu^{A,j} \right)$$

where $\mathbf{D}^{\varphi,j} \equiv \left[\frac{\partial \ln \varphi_g}{\partial \ln A_{jh}}\right]_{gh}$ and $\mathbf{D}^{\phi,j} \equiv \left[\frac{\partial \ln \phi}{\partial \ln A_{jh}}\right]$.

We proceed by applying this approximation to log nominal revenue per unit of time, $\ln x_{ig}(s) \equiv \ln p_{ig}(s) + \ln A_{ig}(s)$. Using expression (9) for prices (ignoring the $D_i(s)$ term since it cancels out in the utility function; see equation (13)), we have:

$$\ln x_{ig}(s) = \frac{1}{\sigma} \ln \alpha_g - \left(\sum_{j=1}^{N} T_{ij} \sum_{k \neq j} \varepsilon_{jk} \right) \left(\ln \bar{\varphi}_g + \sum_{j=1}^{N} \mathbf{D}_g^{\varphi,j} \left(\ln A_j(s) - \mu^{A,j} \right) \right)$$
$$- \sum_{j=1}^{N} T_{ij} \ln \left(\theta_{jg} + A_{jg}(s) \right) + \ln A_{ig}(s).$$

From Assumption (1), the distribution of productivities is log-normal and the log nominal revenue per unit of time is a linear combination of the log productivities, it too is distributed log normally. Using the familiar expression for the distribution of an affine transformation of a normally distributed variable, we have:

$$\ln \mathbf{x}_i \sim N\left(\mu^{x,i}, \Sigma^{x,i} \right),$$

where:

$$\mu_g^{x,i} \equiv \frac{1}{\sigma} \ln \alpha_g - \left(\sum_{j=1}^{N} T_{ij} \bar{\varepsilon}_j \right) \left(\ln \bar{\varphi}_g \right) - \sum_{j=1}^{N} T_{ij} \left(\ln \theta_{jg} + \mu_g^{A,j} \right) + \mu_g^{A,i}$$

$$\Sigma^{x,i} \equiv \left((1 - T_{ii}) \mathbf{I} - \left(\sum_{j=1}^{N} T_{ij} \bar{\varepsilon}_j \right) \mathbf{D}^{\varphi,i} \right) \Sigma^{A,i} \left((1 - T_{ii}) \mathbf{I} - \left(\sum_{j=1}^{N} T_{ij} \bar{\varepsilon}_j \right) \mathbf{D}^{\varphi,i} \right)'$$
$$+ \sum_{j \neq i} \left(\left(\sum_{j=1}^{N} T_{ij} \bar{\varepsilon}_j \right) \mathbf{D}^{\varphi,j} + T_{ij} \mathbf{I} \right) \Sigma^{A,j} \left(\left(\sum_{j=1}^{N} T_{ij} \bar{\varepsilon}_j \right) \mathbf{D}^{\varphi,j} + T_{ij} \mathbf{I} \right)'.$$

Similarly, define $\ln y_{ig}(s) = (1 - \sigma) \ln p_{ig}(s)$. Again using the log-linearization of φ_g and expression (9), we have:

$$\ln \mathbf{y}_i \sim N\left(\mu^{y,i}, \Sigma^{y,i} \right),$$

where:

$$\mu_g^{y,i} \equiv (1 - \sigma) \left(\frac{1}{\sigma} \ln \alpha_g - \left(\sum_{j=1}^{N} T_{ij} \bar{\varepsilon}_j \right) \ln \bar{\varphi}_g - \sum_{j=1}^{N} T_{ij} \left(\ln \theta_{jg} + \mu_g^{A,j} \right) \right)$$

$$\Sigma^{y,i} = (\sigma - 1)^2 \Sigma^{p,i}$$

$$\Sigma^{p,i} = \sum_{j=1}^{N} \left(\left(\sum_{j=1}^{N} T_{ij} \sum_{k \neq j} \varepsilon_{jk} \right) \mathbf{D}^{\varphi,j} + T_{ij} \mathbf{I} \right) \Sigma^{A,j} \left(\left(\sum_{j=1}^{N} T_{ij} \sum_{k \neq j} \varepsilon_{jk} \right) \mathbf{D}^{\varphi,j} + T_{ij} \mathbf{I} \right)'.$$

Given these definitions, note that we can write the (log of) the real returns $Z_i^f(s)$ as:

$$\ln Z_i^f(s) = \ln \sum_{g=1}^{G} \theta_{ig}^f x_{ig}(s) + \frac{1}{\sigma - 1} \ln \sum_{h=1}^{G} \alpha_h y_{ig}(s) + \ln (1 + \phi(s))$$

As in Campbell and Viceira (2002), we now rely on a second-order approximaiton of the log real returns around the mean log productivities. In particular, we write:

$$\ln Z_i^f(s) \approx \left(\ln \sum_{g=1}^{G} \theta_{ig}^f \exp\left\{ \mu_g^{x,i} \right\} - \sum_{g=1}^{G} \theta_{ig}^f \mu_g^{x,i} \right) + \frac{1}{\sigma - 1} \left(\ln \sum_{h=1}^{G} \alpha_h \exp\left\{ \mu_g^{y,i} \right\} - \sum_{h=1}^{G} \alpha_h \mu_g^{y,i} \right)$$
$$+ \sum_{g=1}^{G} \theta_{ig}^f \ln x_{ig}(s) + \frac{1}{\sigma - 1} \sum_{h=1}^{G} \alpha_h \ln y_{ih}(s) + \frac{1}{2} \sum_{g=1}^{G} \theta_{ig}^f \Sigma_{gg}^{x,i} - \frac{1}{2} \sum_{g=1}^{G} \sum_{h=1}^{G} \theta_{ih}^f \theta_{ig}^f \Sigma_{gh}^{x,i}$$
$$+ \frac{1}{2} (\sigma - 1) \sum_{g=1}^{G} \alpha_g \Sigma_{gg}^{p,i} - (\sigma - 1) \frac{1}{2} \sum_{g=1}^{G} \sum_{h=1}^{G} \alpha_g \alpha_h \Sigma_{gh}^{p,i}$$
$$+ \ln (1 + \bar{\phi}) + \sum_{j=1}^{N} \mathbf{D}^{\phi,j} \left(\ln A_j(s) - \mu^{A,j} \right).$$

Again, because the log real returns $\ln Z_i^f(s)$ are an affine transformation of log-normally distributed random variables, the log real returns are also log-normally distributed:

$$\ln Z_i^f \sim N\left(\mu_i^Z, \sigma_i^{2,Z}\right).$$

Taking expectations of this expression gives us the mean:

$$\begin{aligned}\mu_i^Z \equiv& \ln \sum_{g=1}^G \theta_{ig}^f \exp\left\{\mu_g^{x,i}\right\} + \frac{1}{\sigma-1}\ln \sum_{g=1}^G \alpha_g \exp\left\{\mu_g^{y,i}\right\} \\ &+ \frac{1}{2}\left(\sum_g \theta_{ig}^f \Sigma_{gg}^{x,i} - \sum_g\sum_h \theta_{ih}^f\theta_{ig}^f \Sigma_{gh}^{x,i}\right) \\ &+ \frac{1}{2}(\sigma-1)\left(\sum_{g=1}^G \alpha_g \Sigma_{gg}^{p,i} - \frac{1}{2}\sum_{g=1}^G\sum_{h=1}^G \alpha_g\alpha_h \Sigma_{gh}^{p,i}\right) \\ &+ \ln(1+\bar{\phi}),\end{aligned}$$

whereas the variance can be written as:

$$\sigma_i^{2,Z} = \sum_{g=1}^G\sum_{h=1}^G \theta_{ig}^f\theta_{ih}^f \Sigma_{gh}^{z,i},$$

where:

$$\begin{aligned}\Sigma^{z,i} \equiv& \left(\mathbf{I} - \left(T_{ii}\mathbf{B} + \left(\sum_{j=1}^N T_{ij}\bar{\varepsilon}_j\right)\mathbf{B}\mathbf{D}^{\varphi,j} + \tilde{\mathbf{D}}^{\phi,i}\right)\right)\Sigma^{A,i}\left(\mathbf{I} - \left(T_{ii}\mathbf{B} + \left(\sum_{j=1}^N T_{ij}\bar{\varepsilon}_j\right)\mathbf{B}\mathbf{D}^{\varphi,j} + \tilde{\mathbf{D}}^{\phi,j}\right)\right)' \\ &+ \sum_{j\neq i}\left(T_{ij}\mathbf{B} + \left(\sum_{k=1}^N T_{jk}\bar{\varepsilon}_k\right)\mathbf{B}\mathbf{D}^{\varphi,j} + \tilde{\mathbf{D}}^{\phi,i}\right)\Sigma^{A,j}\left(T_{ij}\mathbf{B} + \left(\sum_{k=1}^N T_{jk}\bar{\varepsilon}_k\right)\mathbf{B}\mathbf{D}^{\varphi,j} + \tilde{\mathbf{D}}^{\phi,j}\right)',\end{aligned}$$

as claimed. □

A.5 Proof of Proposition 2

We first restate the proposition:

Proposition. *[Restated] Suppose that the Pareto distribution of trade costs can be written as $\varepsilon_{ij}(t) = \varepsilon_{ij}t$, where $t \geq 0$ captures the overall level of openness of the world and an increase in t indicates a fall in trade costs and there are a large number of villages (so that the equilibrium market tightness is constant across states of the world) Then:*

(1) [Stylized Fact #1] Define $\sigma_{i,Y}^2$ and $\sigma_{i,P}^2$ to be the variance of the log of the numerator and the denominator, respectively, of the real returns $Z_i^f(s)$. Then:

$$\frac{d\sigma_{i,Y}^2}{dt}|_{t=0} > 0 \text{ and } \frac{d\sigma_{i,P}^2}{dt}|_{t=0} < 0,$$

i.e. moving from autarky to costly trade increases the volatility of nominal income and decreases the volatility of prices.

(2) [Stylized Fact #2] Any increase in openness decreases the responsiveness of local prices to local yield

shocks, i.e.:

$$\frac{d}{dt}\left(-\frac{\partial \ln p_{ig}(s)}{\partial \ln A_{ig}(s)}\right) < 0.$$

(3) [Stylized Fact #3] Any increase in openness causes farmers to reallocate production toward crops with higher mean yields. Moreover, as long as farmers are sufficiently risk averse (i.e. ρ_i is sufficiently large and positive), goods are substitutes (i.e. $\sigma \geq 1$), and local prices are not too responsive to local productivity shocks (i.e. $(1 - T_{ii})\theta_{ig} \geq T_{ii}\alpha_g$), then any increase in openness causes farmers to reallocate production toward crops with less volatile yields, although the latter effect is attenuated the greater the access to insurance (i.e. the lower ρ_i). Formally for any two crops $g \neq h$:

$$\frac{d}{dt}\frac{\partial\left(\ln\theta_{ig} - \ln\theta_{ih}\right)}{\partial\mu^A_{ig}} > 0,\ \frac{d}{dt}\frac{\partial\left(\ln\theta_{ig} - \ln\theta_{ih}\right)}{\partial\Sigma^{A,i}_{gg}} \leq 0,\ \textit{and}\ -\frac{d}{dt}\frac{\partial^2\left(\ln\theta_{ig} - \ln\theta_{ih}\right)}{\partial\Sigma^{A,i}_{gg}\partial\rho_i} \geq 0.$$

Proof. [Part 1]. From Proposition 1 that the nominal income $x_{ig}(s) \equiv A_{ig}(s)\, p_{ig}(s)$ is log-normally distributed:

$$\ln \mathbf{x}_i \sim N\left(\mu^{x,i}, \Sigma^{x,i}\right),$$

where:

$$\mu^{x,i}_g \equiv \frac{1}{\sigma}\ln\alpha_g - \left(\sum_{j=1}^N T_{ij}\bar{\varepsilon}_j\right)\left(\ln\bar{\varphi}_g\right) - \sum_{j=1}^N T_{ij}\left(\ln\theta_{jg} + \mu^{A,j}_g\right) + \mu^{A,i}_g$$

$$\Sigma^{x,i} \equiv \left((1 - T_{ii})\,\mathbf{I} - \left(\sum_{j=1}^N T_{ij}\bar{\varepsilon}_j\right)\mathbf{D}^{\varphi,i}\right)\Sigma^{A,i}\left((1 - T_{ii})\,\mathbf{I} - \left(\sum_{j=1}^N T_{ij}\bar{\varepsilon}_j\right)\mathbf{D}^{\varphi,i}\right)'$$
$$+\sum_{j\neq i}\left(\left(\sum_{j=1}^N T_{ij}\bar{\varepsilon}_j\right)\mathbf{D}^{\varphi,j} + T_{ij}\mathbf{I}\right)\Sigma^{A,j}\left(\left(\sum_{j=1}^N T_{ij}\bar{\varepsilon}_j\right)\mathbf{D}^{\varphi,j} + T_{ij}\mathbf{I}\right)'.$$

Applying the same second order approximation as in Proposition 1, we have that the variance of the log nominal income is approximately:

$$\sigma^2_{Y,i} \equiv \sum_{g=1}^G\sum_{h=1}^G \theta_{ig}\theta_{ih}\Sigma^{x,i}_{gh}.$$

Similarly, the variance of the log price index is approximately:

$$\sigma^2_{P,i} \equiv (\sigma - 1)\sum_{g=1}^G\sum_{h=1}^G \alpha_g\alpha_h\Sigma^{p,i}_{gh},$$

where:

$$\Sigma^{p,i} = \sum_{j=1}^N\left(\left(\sum_{j=1}^N T_{ij}\sum_{k\neq j}\varepsilon_{jk}\right)\mathbf{D}^{\varphi,j} + T_{ij}\mathbf{I}\right)\Sigma^{A,j}\left(\left(\sum_{j=1}^N T_{ij}\sum_{k\neq j}\varepsilon_{jk}\right)\mathbf{D}^{\varphi,j} + T_{ij}\mathbf{I}\right)'.$$

If there are many locations (so that $\mathbf{D}^{\varphi,j}=\mathbf{0}$), then these expressions simplify:

$$\Sigma^{x,i}=(1-T_{ii})\,\Sigma^{A,i}+\sum_{j\neq i}T_{ij}^2\Sigma^{A,j}.$$

$$\Sigma^{p,i}=\sum_{j=1}^{N}T_{ij}^2\Sigma^{A,j},$$

so that:

$$\frac{\partial\sigma_{i,Y}^2}{\partial T_{ij}}=\begin{cases}-2\,(1-T_{ii})\sum_g\sum_h\Sigma_{gh}^{A,i}\theta_{ig}\theta_{ih}<0 & \text{if } i=j\\ 2T_{ij}\sum_g\sum_h\Sigma_{gh}^{A,i}\theta_{ig}\theta_{ih}>0 & \text{if } i\neq j\end{cases}$$

and:

$$\frac{\partial\sigma_{P,i}^2}{\partial T_{ij}}=2T_{ij}\sum_{g=1}^{G}\sum_{h=1}^{G}\alpha_g\alpha_h\Sigma_{gh}^{A,j}>0.$$

As a result, we have:

$$\frac{d\sigma_{i,Y}^2}{dt}=\frac{1}{\sigma^2}\left(\sum_{j\neq i}\varepsilon_{ij}\frac{d\sigma_{i,Y}^2}{dT_{ij}}-\sum_{j\neq i}\varepsilon_{ij}\frac{d\sigma_{i,Y}^2}{dT_{ii}}\right)\iff$$
$$\frac{d\sigma_{i,Y}^2}{dt}=\frac{1}{\sigma^2}2\left(\sum_{j\neq i}\varepsilon_{ij}T_{ij}+\sum_{j\neq i}\varepsilon_{ij}\,(1-T_{ii})\right)\sum_g\sum_h\Sigma_{gh}^{A,i}\theta_{ig}\theta_{ih}$$

We also have:

$$\frac{d\sigma_{i,P}^2}{dt}=\frac{1}{\sigma^2}\left(\sum_{j\neq i}\varepsilon_{ij}\frac{d\sigma_{i,P}^2}{dT_{ij}}-\sum_{j\neq i}\varepsilon_{ij}\frac{d\sigma_{i,P}^2}{dT_{ii}}\right)\iff$$
$$\frac{d\sigma_{i,Y}^2}{dt}=\frac{1}{\sigma^2}2\left(\sum_{j\neq i}\varepsilon_{ij}\left(T_{ij}-T_{ii}\right)\right)\sum_{g=1}^{G}\sum_{h=1}^{G}\alpha_g\alpha_h\Sigma_{gh}^{A,j}.$$

Finally, evaluating at $t=0$ yields:

$$\frac{\partial\sigma_{i,Y}^2}{\partial t}|_{t=0}=2\left(\frac{\sigma+\sum_{j\neq i}\varepsilon_{ij}-1}{\sigma+\sum_{j\neq i}\varepsilon_{ij}}\right)\left(\frac{1}{\sigma^2}\sum_{j\neq i}\varepsilon_{ij}\right)\left(\sum_g\sum_h\Sigma_{gh}^{A,i}\theta_{ig}\theta_{ih}\right)>0$$
$$\frac{\partial\sigma_{i,P}^2}{\partial t}|_{t=0}=-2\left(\frac{\sigma+\sum_{j\neq i}\varepsilon_{ij}-1}{\sigma+\sum_{j\neq i}\varepsilon_{ij}}\right)\left(\frac{1}{\sigma^2}\sum_{j\neq i}\varepsilon_{ij}\right)\left(\sum_g\sum_h\Sigma_{gh}^{A,i}\alpha_g\alpha_h\right)<0,$$

as claimed.

[Part 2]. The matrix $\mathbf{T}(t)\equiv\mathbf{E}(t)^{-1}$, where $\mathbf{E}(t)\equiv\sigma\mathbf{I}+\left(diag\left(\boldsymbol{\varepsilon}\mathbf{1}_N+(\varepsilon_{i0})_i\right)-\boldsymbol{\varepsilon}\right)t$ and $\boldsymbol{\varepsilon}$ is the $N\times N$ matrix with zeros on diagonal and ε_{ij} off diagonal. Using the familiar expression for the derivative of an inverse of a matrix, we have:

$$\frac{d\mathbf{T}(t)}{dt}=-\mathbf{E}(t)^{-1}\frac{d\mathbf{E}(t)}{dt}\mathbf{E}(t)^{-1}$$

Since $\mathbf{E}(t)$ is an M-matrix (see above), all elements of its inverse $\mathbf{T}(t)\equiv\mathbf{E}(t)^{-1}$ are strictly positive. Hence we have:

$$\frac{dT_{ii}(t)}{dt} = -\mathbf{T}(t)\, diag\left(\boldsymbol{\varepsilon}\mathbf{1}_N + (\varepsilon_{i0})_i\right)\mathbf{T}(t) < 0$$

since $diag\left(\boldsymbol{\varepsilon}\mathbf{1}_N + (\varepsilon_{i0})_i\right) > 0$. From equation (9), we have $-\frac{\partial \ln p_{ig}(s)}{\partial \ln A_{ig}(s)} = -T_{ii}$, so $\frac{d}{dt}\left(-\frac{\partial \ln p_{ig}(s)}{\partial \ln A_{ig}(s)}\right) < 0$ as claimed.

[Part 3]. Taking logs of equation (17) yields:

$$\ln \theta_{ig} = \ln \alpha_g - \mu_g^{A,i} - \bar{\varepsilon}_i \ln \varphi_g + \sigma \ln b_{ig} + \sum_{j\neq i} \varepsilon_{ij} t \left(\ln b_{ig} - \ln b_{jg}\right) - C_i,$$

where $\ln b_{ig} \equiv \mu_g^{A,i} - \ln\left(\lambda_i - \left(\frac{1}{2}\Sigma_{gg}^{x,i} - \sum_{h=1}^G \theta_{ih}\left(\Sigma_{gh}^{x,i} - \Sigma_{gh}^{z,i}\right) - \rho_i \sum_{h=1}^G \theta_{ih}\Sigma_{gh}^{z,i}\right)\right)$ and the crop-invariant constant $C_i \equiv \ln\left(\sum_{g=1}^G \alpha_g \exp\left(\mu_g^{A,i}\right)^{-1} \bar{\varphi}_g^{-\bar{\varepsilon}_i} b_{ig}^{\sigma} \prod_{j\neq i}\left(\frac{b_{ig}}{b_{jg}}\right)^{\varepsilon_{ij}}\right)$ ensures land constraint holds. Hence, the difference in crop allocation between any two crops $g \neq h$ can be expressed as:

$$\ln \theta_{ig} - \ln \theta_{ih} = \left(\ln \alpha_g - \mu_g^{A,i} - \bar{\varepsilon}_i \ln \varphi_g + \sigma \ln b_{ig} + \sum_{j\neq i} \varepsilon_{ij}\left(\ln b_{ig} - \ln b_{jg}\right)\right) - \left(\ln \alpha_h - \mu_h^{A,i} - \bar{\varepsilon}_i \ln \varphi_h + \sigma \ln b_{ih} + \sum_{j\neq i} \varepsilon_{ij}\left(\ln b_{ih} - \ln b_{jh}\right)\right)$$

Taking the partial derivative with respect to $\mu_g^{A,i}$ (holding constant λ_i) yields:

$$\frac{\partial\left(\ln \theta_{ig} - \ln \theta_{ih}\right)}{\partial \mu_g^{A,i}} = \left(\sigma + \sum_{j\neq i} \varepsilon_{ij} t - 1\right)$$

so that:

$$\frac{d}{dt}\frac{\partial\left(\ln \theta_{ig} - \ln \theta_{ih}\right)}{\partial \mu_g^{A,i}} = \sum_{j\neq i} \varepsilon_{ij} > 0,$$

as required. Similarly, we have:

$$\frac{d}{dt}\frac{\partial\left(\ln \theta_{ig} - \ln \theta_{ih}\right)}{\partial \Sigma_{gg}^{A,i}} = \left(\sum_{j\neq i} \varepsilon_{ij}\right)\frac{\partial \ln b_{ig}}{\partial \Sigma_{gg}^{A,i}}$$

and:

$$\frac{d}{dt}\frac{\partial^2\left(\ln \theta_{ig} - \ln \theta_{ih}\right)}{\partial \Sigma_{gg}^{A,i}\partial \rho_i} = \left(\sum_{j\neq i} \varepsilon_{ij}\right)\frac{\partial^2 \ln b_{ig}}{\partial \Sigma_{gg}^{A,i}\partial \rho_i}$$

Since $\ln b_{ig} \equiv \mu_g^{A,i} - \ln\left(\lambda_i - \left(\frac{1}{2}\Sigma_{gg}^{x,i} - \sum_{h=1}^G \theta_{ih}\left(\Sigma_{gh}^{x,i} - \Sigma_{gh}^{z,i}\right) - \rho_i \sum_{h=1}^G \theta_{ih}\Sigma_{gh}^{z,i}\right)\right)$, we have $sign\left(\frac{\partial \ln b_{ig}}{\partial \Sigma_{gg}^{A,i}}\right) = sign\left(\frac{\partial\left(\frac{1}{2}\Sigma_{gg}^{x,i} - \sum_{h=1}^G \theta_{ih}\left(\Sigma_{gh}^{x,i} - \Sigma_{gh}^{z,i}\right) - \rho_i \sum_{h=1}^G \theta_{ih}\Sigma_{gh}^{z,i}\right)}{\partial \Sigma_{gg}^{A,i}}\right)$ and $sign\left(\frac{\partial^2 \ln b_{ig}}{\partial \Sigma_{gg}^{A,i}\partial \rho_i}\right) = -sign\left(\frac{\partial \sum_{h=1}^G \theta_{ih}\Sigma_{gh}^{z,i}}{\partial \Sigma_{gg}^{A,i}}\right)$. As long as ρ_i is sufficiently large (i.e. producers are risk averse), then $sign\left(\frac{\partial \ln b_{ig}}{\partial \Sigma_{gg}^{A,i}}\right) = -sign\left(\frac{\partial \sum_{h=1}^G \theta_{ih}\Sigma_{gh}^{z,i}}{\partial \Sigma_{gg}^{A,i}}\right)$. Hence, to prove the remainder of Part 3, it only remains to show that $\frac{\partial \sum_{h=1}^G \theta_{ih}\Sigma_{gh}^{z,i}}{\partial \Sigma_{gg}^{A,i}} > 0$, i.e. an increase in the variance of the log yield of crop g increases the total variance of real returns. To see this, we first note that $\sum_{h=1}^{G} \Sigma_{gh}^{z,i}\theta_{ih} = \frac{1}{2}\frac{\partial}{\partial\theta_{ig}} \sum_{g=1}^{G}\sum_{h=1}^{G} \Sigma_{gh}^{z,i}\theta_{ig}\theta_{ih}$. Then, recall from Proposition 1 that the variance-covariance of real returns in location i can be written as:

$$\Sigma^{z,i} \equiv \left(\mathbf{I} - \left(T_{ii}\mathbf{B} + \left(\sum_{j=1}^{N} T_{ij}\bar{\varepsilon}_j\right)\mathbf{B}\mathbf{D}^{\varphi,j} + \tilde{\mathbf{D}}^{\phi,i}\right)\right)\Sigma^{A,i}\left(\mathbf{I} - \left(T_{ii}\mathbf{B} + \left(\sum_{j=1}^{N} T_{ij}\bar{\varepsilon}_j\right)\mathbf{B}\mathbf{D}^{\varphi,j} + \tilde{\mathbf{D}}^{\phi,j}\right)\right)'$$
$$+ \sum_{j\neq i}\left(T_{ij}\mathbf{B} + \left(\sum_{k=1}^{N} T_{jk}\bar{\varepsilon}_k\right)\mathbf{B}\mathbf{D}^{\varphi,j} + \tilde{\mathbf{D}}^{\phi,i}\right)\Sigma^{A,j}\left(T_{ij}\mathbf{B} + \left(\sum_{k=1}^{N} T_{jk}\bar{\varepsilon}_k\right)\mathbf{B}\mathbf{D}^{\varphi,j} + \tilde{\mathbf{D}}^{\phi,j}\right)',$$

where $\mathbf{B} \equiv (\mathbf{I}_G - \mathbf{1}_G\vec{\alpha}')$ is a $G \times G$ matrix (where $\mathbf{1}_G$ is an $G \times 1$ matrix of ones and $\vec{\alpha} \equiv \left[\alpha_g\right]_g$) and $\tilde{\mathbf{D}}^{\phi,j} \equiv \mathbf{1}_G\left(\mathbf{D}^{\phi,j}\right)'$, where $\mathbf{D}^{\phi,j} \equiv \left[\frac{\partial \ln \phi}{\partial \ln A_{jg}}\right]_g$ is a vector of elasticities of the return to farmers from traders to the productivity shocks in village j. With a large number of villages (so that the $\mathbf{D}$ matrices are equal to zero) and noting that the variance-covariance matric of local yields only enters the first term, we have:

$$\begin{aligned}
\frac{\partial}{\partial\Sigma_{gg}^{A,i}}\sum_{h=1}^{G}\Sigma_{gh}^{z,i}\theta_{ih} &= \frac{1}{2}\frac{\partial^2}{\partial\Sigma_{gg}^{A,i}\partial\theta_{ig}}\sum_{g=1}^{G}\sum_{h=1}^{G}\Sigma_{gh}^{z,i}\theta_{ig}\theta_{ih} \iff \\
&= \frac{1}{2}\frac{\partial^2}{\partial\theta_{ig}}\frac{\partial}{\partial\Sigma_{gg}^{A,i}}\sum_{g=1}^{G}\sum_{h=1}^{G}\Sigma_{gh}^{z,i}\theta_{ig}\theta_{ih} \iff \\
&= \frac{1}{2}\frac{\partial}{\partial\theta_{ig}}\left(\frac{\partial}{\partial\Sigma_{gg}^{A,i}}\vec{\theta}_i\left(\mathbf{I} - T_{ii}\mathbf{B}\right)\Sigma^{A,i}\left(\mathbf{I} - T_{ii}\mathbf{B}\right)'\vec{\theta}_i\right) \iff \\
&= \frac{1}{2}\frac{\partial}{\partial\theta_{ig}}\left(\frac{\partial}{\partial\Sigma_{gg}^{A,i}}\vec{\theta}_i'\left(\left(1 - T_{ii}\right)\mathbf{I} - T_{ii}\mathbf{1}_G\vec{\alpha}'\right)\Sigma^{A,i}\left(\left(1 - T_{ii}\right)\mathbf{I} - T_{ii}\mathbf{1}_G\vec{\alpha}'\right)'\vec{\theta}_i\right) \iff \\
&= \frac{1}{2}\frac{\partial}{\partial\theta_{ig}}\left(\frac{\partial}{\partial\Sigma_{gg}^{A,i}}\sum_{h,l=1}^{G}\left(\left(1 - T_{ii}\right)^2\Sigma_{hl}^{A,i} - \left(1 - T_{ii}\right)T_{ii}\sum_{k=1}^{G}\alpha_k\left(\Sigma_{hk}^{A,i} + \Sigma_{kl}^{A,i}\right) + T_{ii}^2\sum_{l,k=1}^{G}\Sigma_{lk}^{A,i}\alpha_l\alpha_k\right)\theta_{ih}\theta_{il}\right) \\
&= \frac{1}{2}\frac{\partial}{\partial\theta_{ig}}\left(\left(1 - T_{ii}\right)^2\theta_{ig}^2 - 2\left(1 - T_{ii}\right)T_{ii}\alpha_g\theta_{ig} + T_{ii}^2\alpha_g^2\right) \iff \\
&= \frac{1}{2}\frac{\partial}{\partial\theta_{ig}}\left(\left(1 - T_{ii}\right)\theta_{ig} - T_{ii}\alpha_g\right)^2 \iff \\
&= \left(\left(1 - T_{ii}\right)\theta_{ig} - T_{ii}\alpha_g\right)\left(1 - T_{ii}\right)
\end{aligned}$$

Note that $T_{ii} \leq 1$ as long as $\sigma \geq 1$ (since $\sum_{j=1}^{N} T_{ij} = \frac{1}{\sigma}$) so we have that:

$$\left(1 - T_{ii}\right)\theta_{ig} \geq T_{ii}\alpha_g \implies \frac{\partial}{\partial\Sigma_{gg}^{A,i}}\sum_{h=1}^{G}\Sigma_{gh}^{z,i}\theta_{ih} \geq 0,$$

as required. □

A.6 Approximating the matrix T of price elasticities

In this subsection, we describe how we approximate the matrix $\mathbf{T}$ of price elasticities. Recall that $\mathbf{T} \equiv \mathbf{E}^{-1}$, where:

$$\mathbf{E} = \begin{cases} \sum_{j \neq i} \varepsilon_{ij} + \sigma & \text{if } i = j \\ -\varepsilon_{ij} & \text{o/w} \end{cases}.$$

Because $\mathbf{E}$ is diagonally dominant with negative off-diagonal elements and positive diagonal elements, it is an M-matrix. Because $\mathbf{E}$ is an M-matrix, it can be expressed as $\mathbf{E} = \kappa\mathbf{I} - \mathbf{B}$, where $\mathbf{I}$ is an identity matrix, $\mathbf{B} = \left[B_{ij}\right]$ where $B_{ij} \geq 0$, and κ is greater than the maximum eigenvalue of $\mathbf{B}$ (see e.g. Plemmons (1977) for a discussion of the many properties of M-matrices). Define $\tilde{\mathbf{E}} \equiv \frac{1}{\kappa}\mathbf{E}$ and $\tilde{\mathbf{B}} \equiv \frac{1}{\kappa}\mathbf{B}$. Note that $\tilde{\mathbf{E}} = \mathbf{I} - \tilde{\mathbf{B}}$ is also an M-matrix and $\tilde{\mathbf{B}}$ has a maximum eigenvalue smaller than 1.

Note that $\mathbf{T} = \mathbf{E}^{-1} = \left(\kappa\tilde{\mathbf{E}}\right)^{-1} = \frac{1}{\kappa}\tilde{\mathbf{E}}^{-1}$. Furthermore, recall that because $\tilde{\mathbf{B}}$ has a maximum eigenvalue smaller than 1, the following representation its geometric infinite sum holds:

$$\sum_{k=0}^{\infty} \tilde{\mathbf{B}}^k = \left(\mathbf{I} - \tilde{\mathbf{B}}\right)^{-1} = \tilde{\mathbf{E}}^{-1}.$$

Hence we can write the matrix of price elasticities as an infinite sum of the (appropriately scaled) matrix of bilateral Pareto shape parameters:

$$\mathbf{T} = \frac{1}{\kappa}\sum_{k=0}^{\infty}\left(\mathbf{I} - \frac{1}{\kappa}\mathbf{E}\right)^k.$$

A first order approximation of $\mathbf{T}$ is hence:

$$\mathbf{T} \approx \frac{2}{\kappa}\mathbf{I} - \frac{1}{\kappa^2}\mathbf{E} \iff$$
$$T_{ij} \approx \begin{cases} \frac{1}{\kappa^2}\left(2\kappa - \sigma - \sum_{j \neq i} \varepsilon_{ij}\right) & \text{if } i = j \\ \frac{1}{\kappa^2}\varepsilon_{ij} & \text{o/w} \end{cases}$$

Using this approximation in the estimating equation results in:

$$\ln p_{igt} = -\sum_{j=1}^{N} T_{ij} \ln A_{jgt} + \delta_{it} + \delta_{ig} + \delta_{gt} + \nu_{igt} \iff$$
$$\ln p_{igt} = -\frac{1}{\kappa^2}\left(2\kappa - \sigma\right) \ln A_{igt} - \frac{1}{\kappa^2}\sum_{j \neq i} \varepsilon_{ij} \ln\left(\frac{A_{jgt}}{A_{igt}}\right) + \delta_{it} + \delta_{ig} + \delta_{gt} + \mu_{igt}$$

Finally, if we assume that the Pareto shape parameters are parametrized by travel time D_{ij}, i.e. $\varepsilon_{ij} = \beta D_{ij}^{-\phi}$, where β is an unknown parameter, we can write:

$$\ln p_{igt} = -\gamma_1 \ln A_{igt} - \gamma_2 \sum_{j \neq i} D_{ij}^{-\phi} \ln\left(\frac{A_{jgt}}{A_{igt}}\right) + \delta_{it} + \delta_{ig} + \delta_{gt} + \mu_{igt},$$

where $\gamma_1 \equiv \frac{1}{\kappa^2}\left(2\kappa - \sigma\right)$ and $\gamma_2 \equiv \frac{\beta}{\kappa^2}$, as claimed in the main text.

A.7 Additional Tables and Figures

Table 9: CROP CHOICE AND OPENNESS (YIELDS INSTRUMENTED WITH RAINFALL)

Dependent variable:	Fraction of land planted by crop						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				phi=1	phi=1	alt. speed	alt. speed
Log(Mean Yield)	0.006***	-0.020***	-0.023***	-0.035***	-0.034***	-0.017***	-0.019***
	(0.002)	(0.004)	(0.005)	(0.006)	(0.007)	(0.004)	(0.005)
Log(Variance Yield)	-0.001*	0.004***	0.005**	0.006***	0.005*	0.003**	0.004*
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.001)	(0.002)
Log(Mean)XMA		0.042***	0.043***	0.016***	0.015***	0.040***	0.039***
		(0.006)	(0.008)	(0.002)	(0.003)	(0.006)	(0.007)
Log(Var)XMA		-0.008***	-0.007**	-0.003***	-0.002	-0.007***	-0.006*
		(0.002)	(0.003)	(0.001)	(0.001)	(0.002)	(0.004)
Log(Mean)XBank			0.484		0.134		0.405
			(0.609)		(0.924)		(0.566)
Log(Var)XBank			-0.306		-0.068		-0.220
			(0.295)		(0.426)		(0.285)
Log(Mean)XMAXBank			-0.242		0.164		0.141
			(0.930)		(0.374)		(0.947)
Log(Var)XMAXBank			0.017		-0.094		-0.089
			(0.458)		(0.179)		(0.485)
Crop-decade FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District-decade FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Crop-district FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.974	0.974	0.974	0.974	0.974	0.974	0.974
Observations	13790	13790	13765	13790	13765	13790	13764
First-stage F stat	193.542	30.381	1.211	78.864	2.562	31.744	1.054

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. Mean and variance of yield instrumented with mean and variance of yield predicted from rainfall variation and district-crop fixed effects (allowing coefficients on rainfall to vary by crop, state and decade). Interaction terms instrumented by predicted yield terms interacted with market access and bank access. 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 10: EXAMPLES OF RELATIONSHIP VOLATILITY, INSURANCE AND THE GAINS FROM TRADE

EXAMPLE 1: Average productivity is the same in both villages

	Autarky	Trade	Gains from Trade
No volatility			
Village 1	0	0	0
Village 2	0	0	0
Volatility			
Village 1	-0.125	-0.1032	0.0218
Village 2	0	0.0201	0.0201

EXAMPLE 2: Comparative advantage goods are risky

	Autarky	Trade	Gains from Trade
No volatility			
Village 1	0	0.7273	0.7273
Village 2	0	0.7273	0.7273
Volatility			
Village 1	-0.125	-0.125	0
Village 2	-0.125	-0.125	0

Notes: This table reports the welfare of each village for the examples discussed in Proposition 2 in Section 4.5. In each example, we calculate the gains from trade (i.e. the difference between welfare with costly trade and in autarky) when productivity is deterministic and when productivity is volatile. In example 1, two villages have the same (unit) mean of two goods. In autarky, $\epsilon = 0$, whereas in trade $\epsilon = 1$. With volatility, $\Sigma_{11}^{A,1} = 1$ and $\mu_{11} = 0.5$ to keep the average yield constant. In example 2, the $\mu_{11} = 1$, $\mu_{12} = 0$, $\mu_{21} = 0$, and $\mu_{22} = 0$ so that village 1 (2) has a comparative advantage in good A (B). With volatility, we set $\Sigma_{11}^{A,1} = 1$ and $\Sigma_{22}^{A,1} = 1$ and reduce the log mean yield of those two goods to 0.5 to keep average yield constant. In both examples, demand is Cobb-Douglas with equal expenditure shares and the risk aversion parameter $\rho = 2$. See the text in Section 4.5 for the intuition behind the results.

Table 11: ESTIMATES CROP COSTS AND ACTUAL CROP COSTS

Dependent variable:	Estimated Crop Costs (Log)	
	(1)	(2)
Actual Crop Costs (Log)	1.379***	1.379**
	(0.314)	(0.571)
Decade FE	Yes	Yes
Crop FE	Yes	Yes
State-Decade-Crop Clustered SEs	No	Yes
R-squared	0.331	0.331
Observations	3021	3021

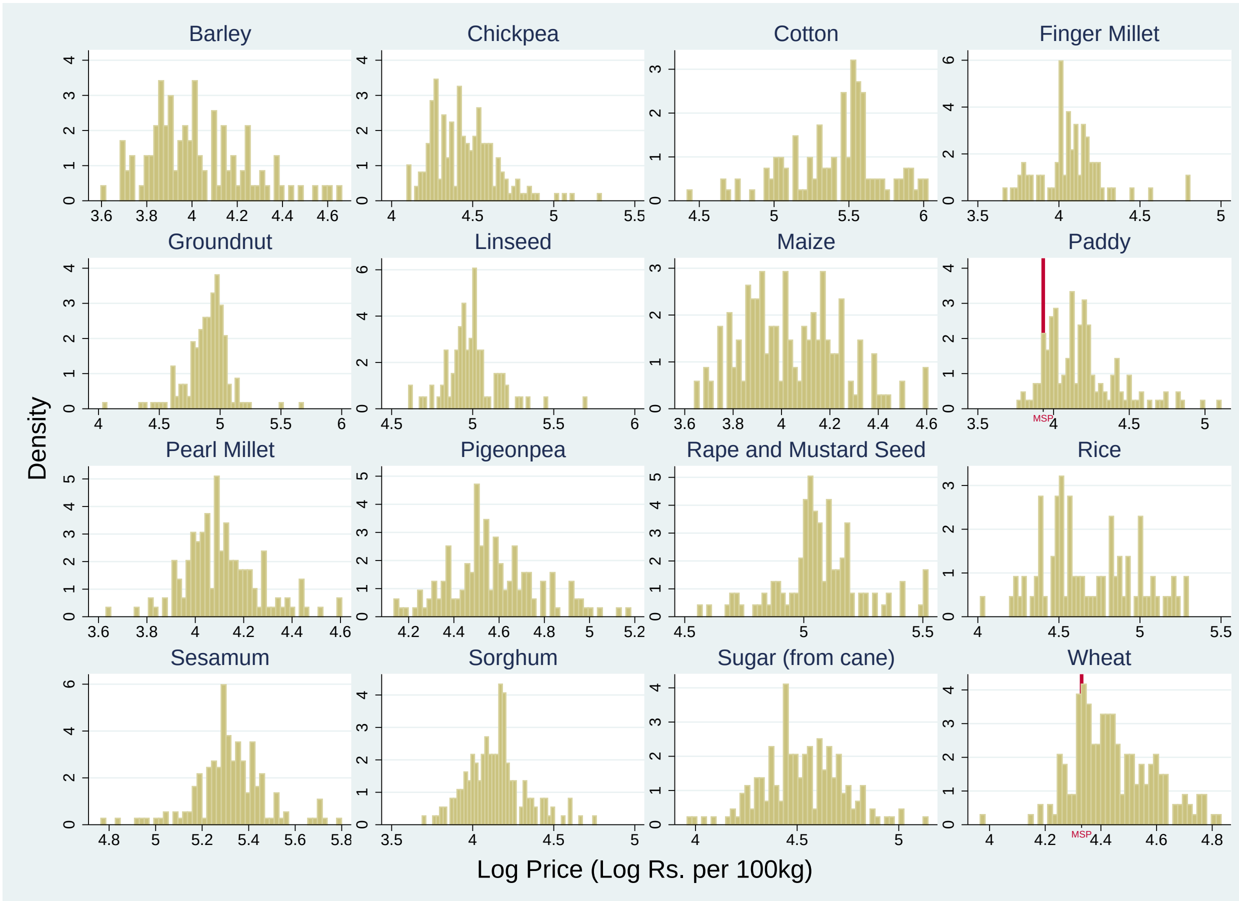
Notes: Regression of the log of estimated crop costs on the log of actual state-level crop costs, decade fixed effects and crop fixed effects. Each observation is a crop-district-decade log crop cost. Estimated crop costs come from a combination of fixed effects and residuals from regression 24 which are the unobserved crop costs that ensure that observed crop choices in the data are optimal crop choices in the model. Raw data on actual crop costs in Rupees/Hectare come from the Government publication *Cost of Cultivation of Principal Crops in India*. Data are annual at the state-crop level and cover 13 of our 15 crops between 1983-2008. To match with the crop-decade level estimated crop costs, actual costs are deflated by the all-India CPI and averaged over decades for each crop and state. Standard errors are reported in parentheses. As the actual crop costs are only at the State level, column 2 clusters standard errors at the state-decade-crop level. Stars indicate statistical significance: * p<.10 ** p<.05 *** p<.01.

Table 12: CROP CHARACTERISTICS AND THE RESPONSE OF CROP ALLOCATIONS TO THE INDIAN HIGHWAY EXPANSION

	Change across decades		Change between 1970s and 2000s	
	(1)	(2)	(3)	(4)
Log of std.dev. of	-0.058***	-0.065***	-0.054	-0.052
1970s log yields	(0.020)	(0.022)	(0.035)	(0.038)
Log of mean of 1970s	0.216*	0.332**	0.744***	0.739**
log yields	(0.130)	(0.166)	(0.212)	(0.305)
Crop-decade FE	Yes	Yes	Yes	Yes
District FE	No	Yes	No	Yes
R-squared	0.183	0.256	0.025	0.187
Observations	10155	10155	3385	3381

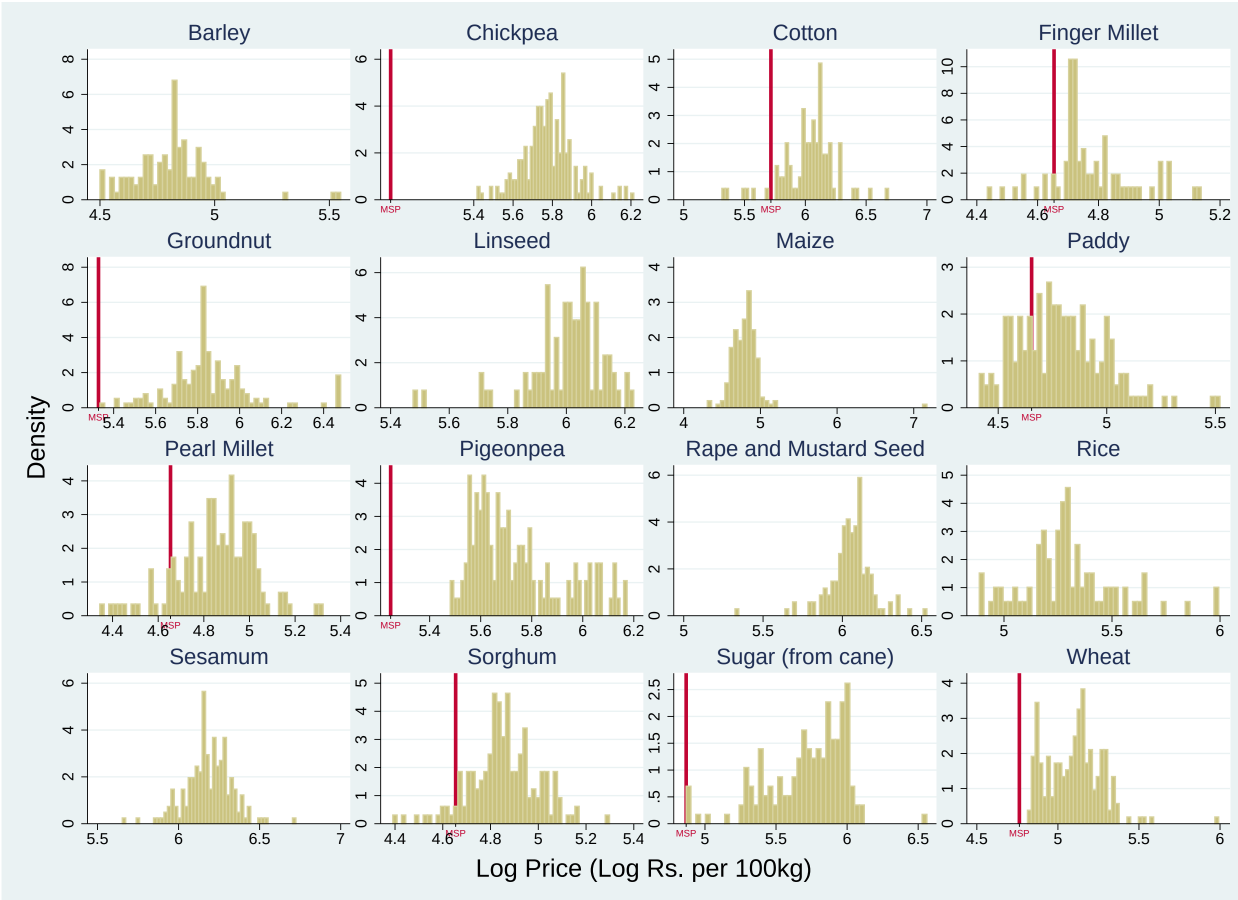
Notes: Ordinary least squares. The dependent variable is the change of the log of the optimal fraction of labor (as calculated by the model) allocated between time periods in response to the expansion of the highway network holding all other parameters fixed, where the difference is either taken across decades (in columns 1 and 2) or between the 1970s and the 2000s (in columns 3 and 4). Each observation is a district-crop-decade triplet. Standard errors clustered at the district level are reported in parentheses. Stars indicate statistical significance: * p<.10 ** p<.05 *** p<.01.

Figure 5: Distribution of Prices and MSPs in 1970-71



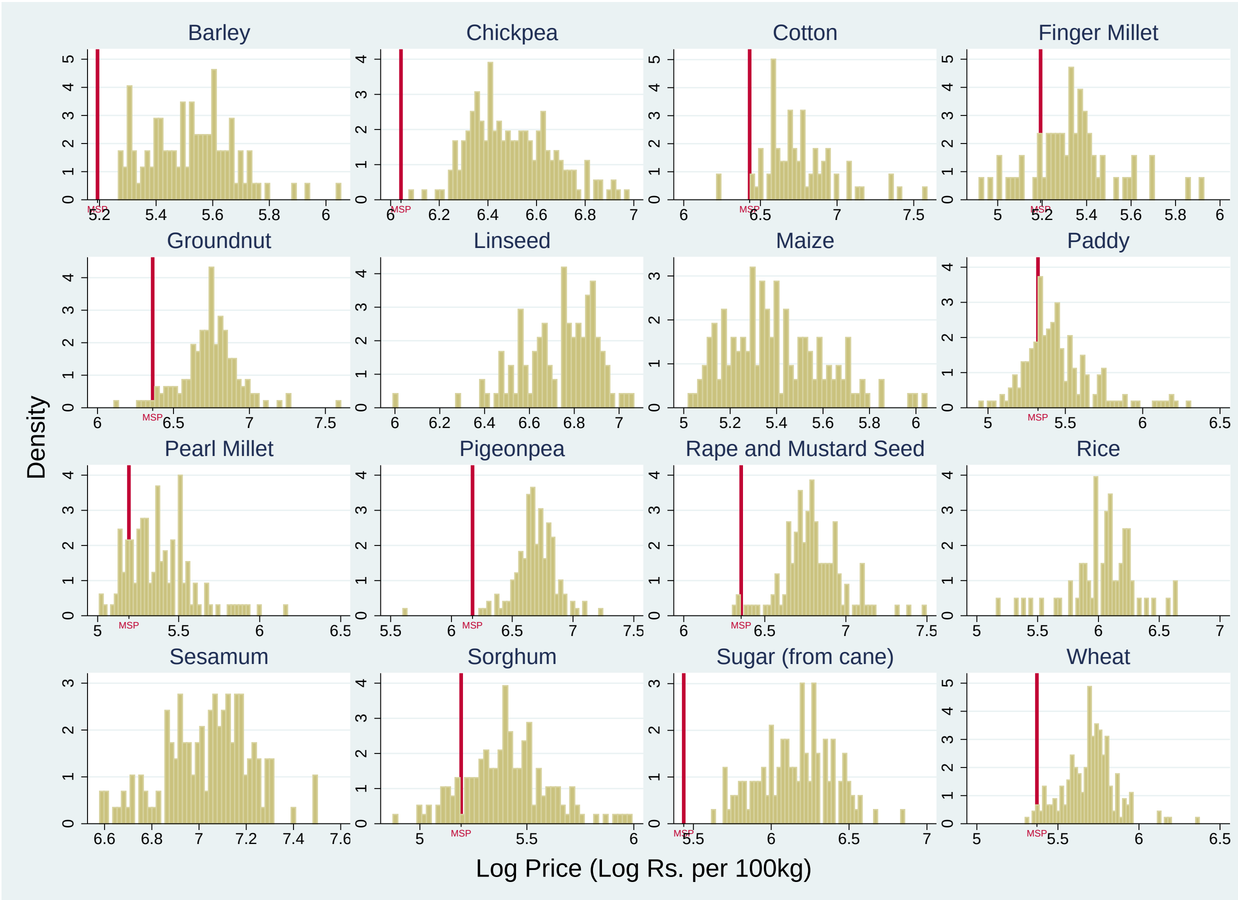
Notes: This figure plots the distribution of log prices across districts for our sample crops in the 1970-71 crop year. Vertical lines show minimum support prices (MSPs) for crops with MSPs in 1970-71.

Figure 6: Distribution of Prices and MSPs in 1980-81



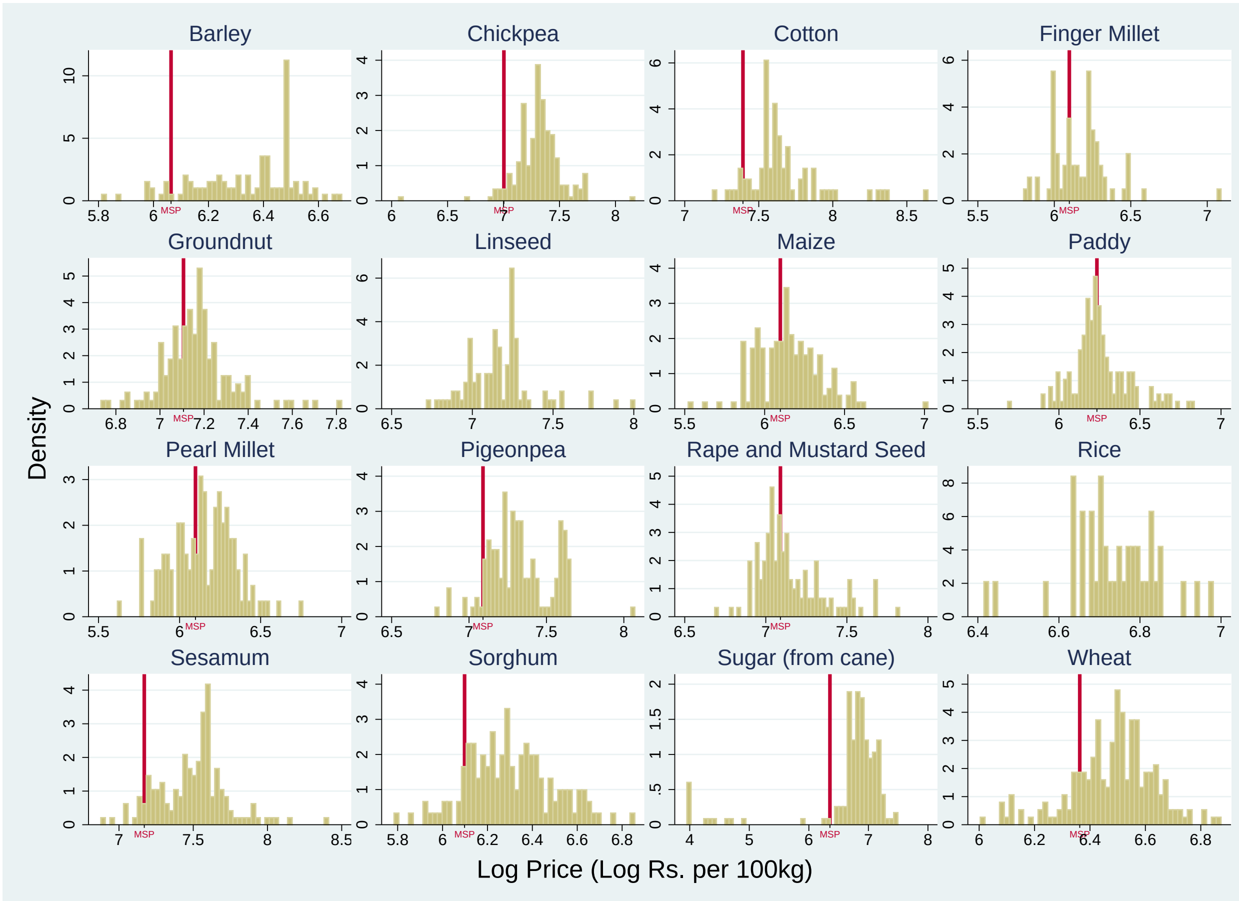
Notes: This figure plots the distribution of log prices across districts for our sample crops in the 1980-81 crop year. Vertical lines show minimum support prices (MSPs) for crops with MSPs in 1980-81.

Figure 7: Distribution of Prices and MSPs in 1990-91



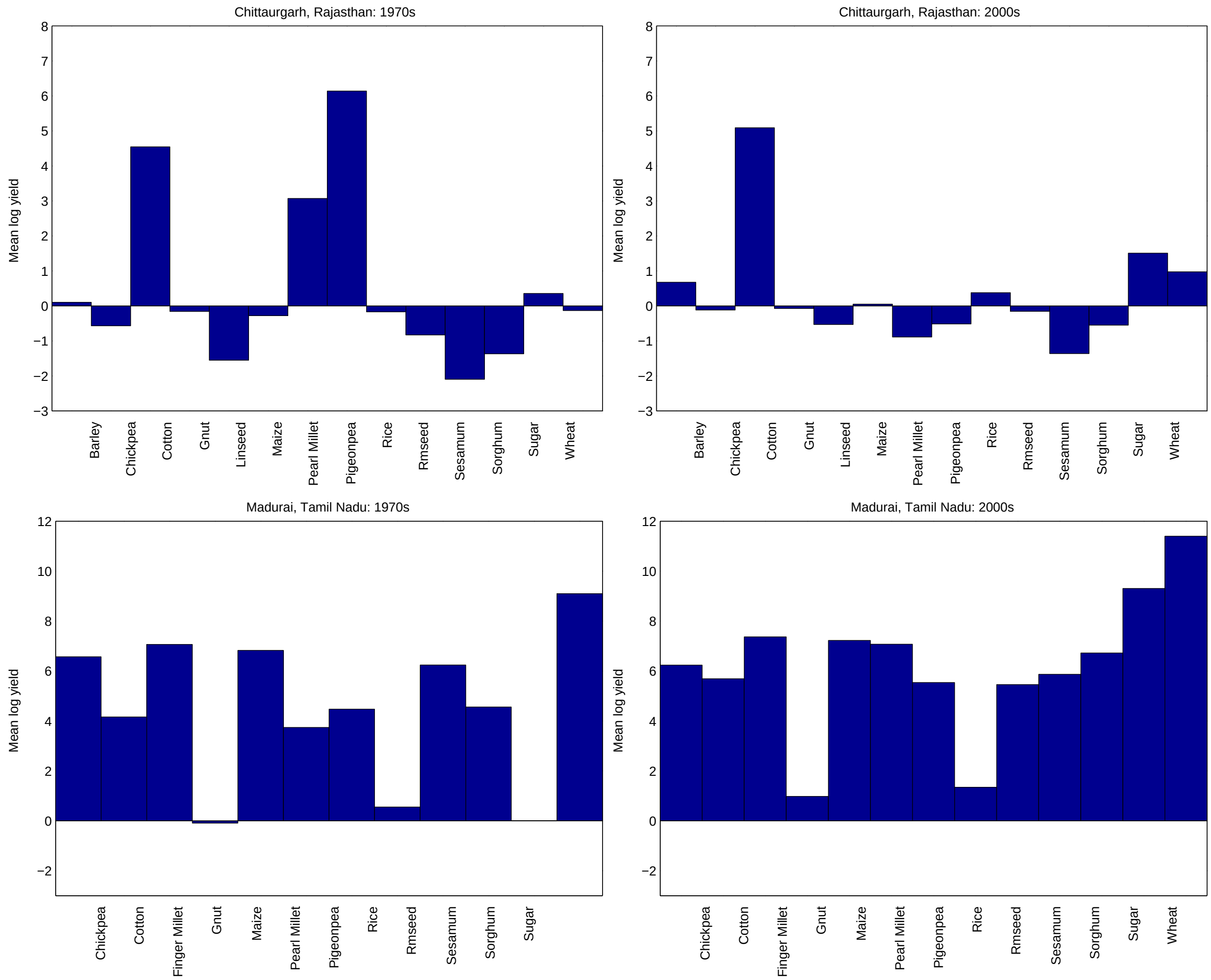
Notes: This figure plots the distribution of log prices across districts for our sample crops in the 1970-71 crop year. Vertical lines show minimum support prices (MSPs) for crops with MSPs in 1990-91.

Figure 8: Distribution of Prices and MSPs in 2000-01



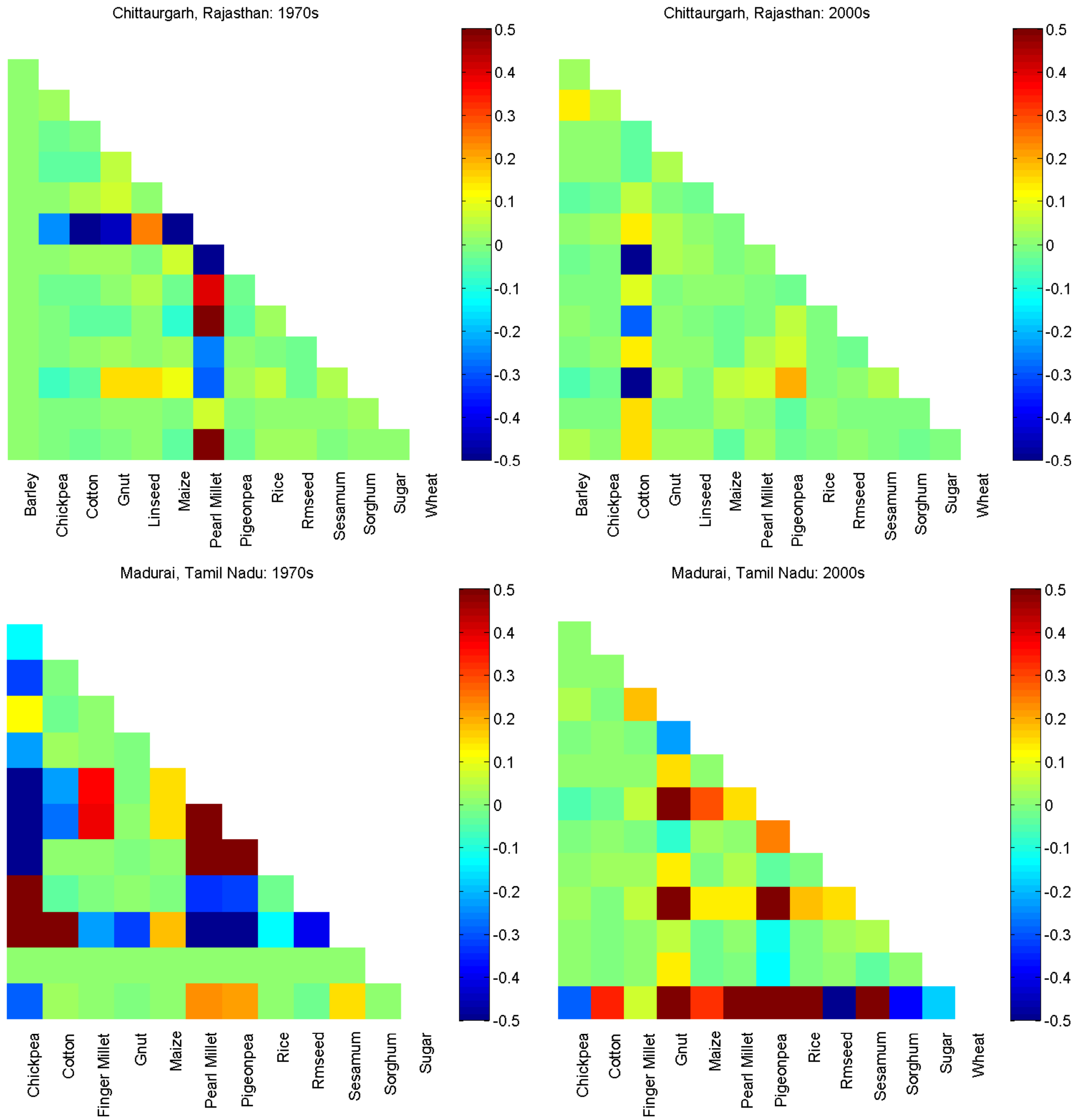
Notes: This figure plots the distribution of log prices across districts for our sample crops in the 2000-01 crop year. Vertical lines show minimum support prices (MSPs) for crops with MSPs in 2000-01.

Figure 9: Mean of yields: Examples



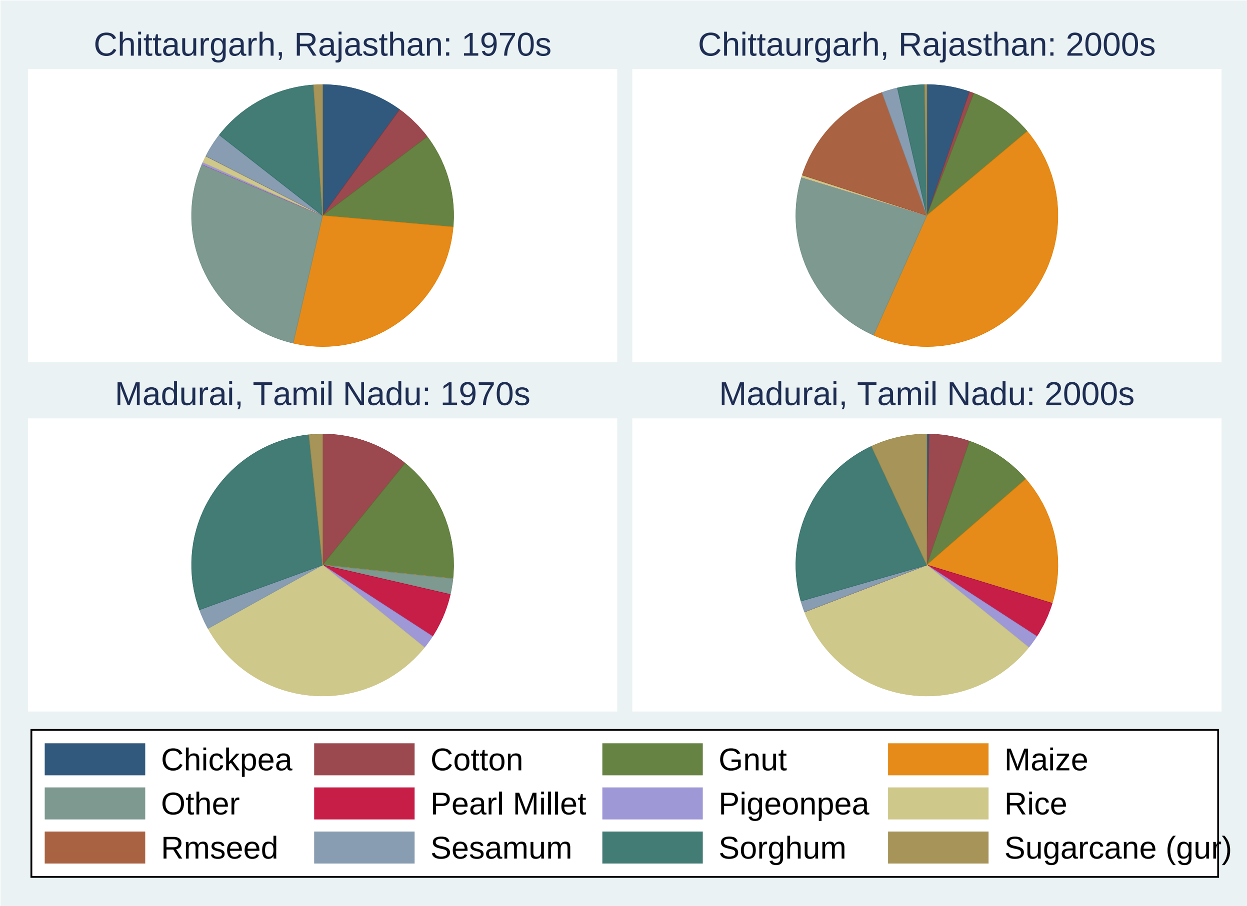
Notes: This figure shows the mean of (log) yields across crops for two example districts—Chittargarh, Rajasthan (top row) and Madurai, Tamil Nadu (bottom row)—in both the 1970s (left column) and the 2000s (right column).

Figure 10: 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 11: 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).