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Trade liberalization changes the volatility of returns by reducing the negative correlation between local prices and productivity shocks. In this paper, we explore these second-moment effects of trade. Using forty years of agricultural micro-data from India, we show that falling trade costs due to expansions of the Indian highway network reduced the responsiveness of local prices to local yields but increased the responsiveness of local prices to yields elsewhere. In response, farmers shifted their production toward crops with less volatile yields, especially so for those with poor access to risk mitigating technologies such as banks. We then characterize how volatility affects farmers' crop allocation using a portfolio choice framework 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' risk-return preferences from the gradient of the mean-variance frontier at their observed crop choices—to quantify the second-moment effects of trade. The simultaneous expansion of both the highway and rural bank networks increased the mean and the variance of farmer real income, with the first-moment effect dominating such that expected welfare rose 4.4%. But had rural bank access remained unchanged, welfare gains would have been only half as great, as risk mitigating technologies allowed farmers to take advantage of higher-risk higher-return allocations.

KEYWORDS: Trade and risk, heterogeneous traders, agricultural trade, portfolio choice, mean-variance frontier, crop choice, India.

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 have

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a limited empirical understanding of the relationship between trade and volatility. In particular, does volatility magnify or attenuate the gains from trade; how do agents respond to changes in the risk they face arising from falling trade costs; and can complementary policies ensure that the gains from trade are maximized?

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 expansions of the Indian highway network reduced the responsiveness of local prices to local rainfall but increased the responsiveness of local prices to yields elsewhere. In response, farmers not only moved toward crops in which they had a comparative advantage, they also shifted their production toward crops with less volatile yields, an effect that was especially strong for farmers with poor access to the formal banking sector. We then incorporate a portfolio allocation framework—where producers optimally allocate resources (land) across risky production technologies (crops)—into a many-location, many-good, general equilibrium Ricardian trade model. The model yields analytical expressions for the equilibrium prices and crop allocations 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 first-moment gains from specialization outweigh any second-moment losses and that improvements in risk mitigating technologies encourage farmers to choose higher-risk higher-return crop allocations that they would otherwise have been unwilling to pursue.

Rural India is our empirical setting, home to roughly one-third of the world's poor and an environment where agricultural 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 limited, forcing farmers—who comprise more than three-quarters of the economically active population—to face the brunt of the volatility. 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 as well as reductions in tariffs) has amplified the risk faced by farmers. These concerns, and the importance of better understanding the link between trade and volatility, are well illustrated by the fact that the Doha round of global trade negotiations collapsed over India and China's insistence on special safeguard mechanisms to protect their farmers; and, more recently, by massive year-long farmer protests over proposals to improve the efficacy of India's agricultural markets by liberalizing the 60-year-old mandi system that restricts agricultural trade within India.

Using a data set containing the annual price, yield, and area planted for 15 major crops across 311 districts and 40 years matched to bilateral travel times along the evolving national highway network, we document three sets of stylized facts. First, reductions in trade costs due to the expansion of the highway network reduced the elasticity of local prices to local yield shocks and increased the elasticity of local prices to yields elsewhere. Second, this fall in trade costs not only caused farmers to reallocate toward crops for which they had a comparative advantage, as traditional trade models would predict; it also caused farmers to reallocate away from risky crops that had more volatile yields and/or yields that had higher covariances with other crops, an effect that was particularly pronounced in districts with poor bank access. Third, the combination of the previous two effects increased the volatility of farmers' nominal incomes, an effect only partially offset by a decline in price index volatility.

We next develop a general equilibrium Ricardian model of trade and volatility that both captures many of the key features of agricultural trade in India and explains the three sets of stylized facts. In the model, heterogeneous traders engage in the buying and selling of homogeneous agricultural goods to take advantage of price differences between local villages and a central market. To circumvent the familiar difficulties arising from corner solutions in determining prices and patterns of specialization, we assume that the distribution of trade costs these traders face takes a convenient Pareto form. This assumption allows equilibrium prices to be written as a log-linear function of the local yield and the market price—consistent with the empirical specification in our first stylized fact—with the relative magnitude of these elasticities governed by the shape parameter of the Pareto distribution of trade costs. This model-implied relationship between prices and yields more closely matches the patterns in the data compared to the "kinked" relationship between prices and yields implied by traditional price arbitrage models with homogeneous trade costs. Furthermore, in the absence of volatility, this model generates a simple expression for the equilibrium pattern of specialization—highlighting that, as trade costs fall, farmers will reallocate their crops away from those they wish to consume and toward those in which they have a comparative advantage in production.

Incorporating volatility into the model poses additional challenges. To derive the equilibrium pattern of specialization in the presence of volatility, we embed a portfolio choice problem from the finance literature (see, e.g., Campbell and Viceira (2002)) into our Ricardian trade framework. In contrast to finance applications, the general equilibrium nature of our trade model means that each farmer's decision depends on the distribution of yields of all crops in all locations and the crop choices of all other farmers. Despite this complication, our expression for the pattern of specialization remains tractable and is a straightforward generalization of the no volatility case. Consistent with the second stylized fact, as trade costs fall, farmers reallocate their land toward crops for which they have a risk adjusted comparative advantage. In doing so, they balance traditional "first-moment" gains from trade against "second-moment" changes in volatility, with the trade-off governed by their level of risk aversion. The model also allows us to sign the effect of a fall in trade costs on the variance of farmers' nominal incomes and the variance of their price index, with the former rising and the latter falling, consistent with the third stylized fact.

Finally, we extend the framework to create a "quantitative" version of the model that adds realism by incorporating a number of additional features of the empirical setting (e.g., a hierarchical trading network featuring many different regional markets, arbitrary correlations in yields across crops and districts, and a manufacturing sector). We then estimate this extended model and use it to quantify the welfare effects of the expansion of the Indian highway network. Despite the added complexity, the tractability of the model allows us to recover the key parameters from the data in a transparent manner. First, as the model implies that the magnitudes of the elasticities of local prices to local yields and prices elsewhere are governed by the distribution of traders' costs, we can recover unobserved trade costs via a linear regression. These trade costs fall with the increases in market access due to highway expansion. Second, as farmers' unobserved risk-return preferences shape the gradient of the mean-variance frontier at the observed crop choices, we can estimate farmers' risk aversion from a linear regression derived from their first-order conditions. We find that these risk aversion estimates fall as rural bank access improves, consistent with banks providing a risk mitigation technology that allows farmers to behave in a less risk averse manner.

We use these parameter estimates to quantify the welfare effects of the expansion of the Indian highway network. Between the 1970s and 2000s, we estimate that the expansion of the Indian highways alone (i.e., holding constant farmers' access to banks) raised the mean real income of farmers by 2.2%, accompanied by a small decline in the volatility of farmers' real incomes as improved market integration elsewhere stabilized market prices. However, when combined with the observed expansion in rural bank access, we find farmers' real income volatility increased, consistent with our third stylized fact. This increase comes from farmers pursuing higher-risk higher-return crop allocations that, in the absence of improvements in risk mitigating technologies, they would have been unwilling to undertake. As a result, the combination of highway expansions and improved rural bank access boosted real incomes (a 2.8% gain vs. 2.2%) and almost doubled the welfare gains (4.4% vs 2.3%) compared to highway expansions alone, with the strength of complementarities hinging on whether the riskiest crops are also the comparative advantage ones.

This paper relates to a number of strands of literature in both international trade and economic development. There is a longstanding theoretical literature on trade and volatility; see Helpman and Razin (1978) and references cited therein. In a seminal paper, Newbery and Stiglitz (1984) developed a stylized model where trade can reduce welfare in the absence of insurance (although, to obtain this stark result, they assumed farmers and consumers differ in their preferences and do not consume what they produce).[1] In our baseline model, farmers are able to produce all goods they consume and so trade always increases their welfare even in the presence of volatility as in Dixit and Norman (1980). That said, the lack of risk sharing between agents producing different types of goods is an important mechanism through which trade may have deleterious second-moment effects; see, for example, Rodrik (1997). Thus, our quantification extends the model to include an urban manufacturing sector to allow for the possibility of welfare losses for farmers. More generally, our paper incorporates the intuition developed in these seminal works into a quantitative trade model that is sufficiently flexible (e.g., many goods and locations with arbitrary variances and covariances of returns and flexible trade costs) to be taken to the data.

Recently, several papers have explored the links between macro-economic volatility and trade; see, for example, Easterly, Islam, and Stiglitz (2001), di Giovanni and Levchenko (2009), Karabay and McLaren (2010), Lee (2018). Our paper instead focuses on the link between micro-economic volatility—that is, good-location specific productivity shocks—and trade. Most closely related to our paper are three papers exploring volatility through the lens of the canonical Eaton and Kortum (2002) framework. Burgess and Donaldson (2010, 2012) studied the relationship between famines and railroads in Colonial India. Like us, they found that infrastructure improvements reduced the responsiveness of local prices and increased the responsiveness of real income to rainfall shocks.[2] Caselli, Koren, Lisicky, and Tenreyro (2019) quantified the relative importance of sectoral and cross-country specialization in a world of globally sourced intermediate goods. We see our paper as having three distinct contributions relative to these papers. First, we depart from Eaton and Kortum (2002), instead developing an alternative quantitative general equilibrium framework that allows us to analyze the pattern of trade while more closely matching several important characteristics of the empirical setting we consider (e.g., homogeneous goods, a hierarchical trading network, and heterogeneous traders). Second, by embedding a portfolio allocation decision where real returns are determined in a general equilibrium trade setting, we characterize the endogenous response of agents

[1]Eaton and Grossman (1985) and Dixit (1987, 1989a,b) incorporated imperfect insurance and incomplete markets.

[2]There are important differences between Colonial and modern India, notably that trade costs may have risen between the two periods. As evidence for this claim, we find local rainfall shocks affect local prices in our sample period 1970–2010 (consistent with substantial barriers to trade across locations), while Donaldson (2018) found they did not in Colonial India post railway construction (consistent with low barriers to trade across locations).

to trade-induced changes in their risk profile. Third, we empirically validate that farmers' land allocation decisions respond as the model predicts.

The paper is also related to a growing literature applying quantitative trade models to the study of agriculture in the absence of volatility. Much of this literature also builds off Eaton and Kortum (2002) (see, e.g., Sotelo (2020), Costinot and Donaldson (2016), Costinot, Donaldson, and Smith (2016), and Bergquist, Faber, Fally, Hoelzlein, Miguel, and Rodriguez-Clare (2019)) with model tractability arising from assuming each location is heterogeneous in its productivity across a continuum of crop varieties or a continuum of plots of land. In contrast, we obtain tractability from traders facing heterogeneous costs of trading, consistent with the empirical setting we consider.[3] This trader heterogeneity generates a new and intuitive arbitrage condition governing price dispersion across locations, which performs better at matching observed price differentials compared to standard conditions based on homogeneous trade costs.

Finally, the paper relates to three 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, we build on 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)). Third, we add to a primarily reduced form literature analyzing the impacts of infrastructure investment (e.g., Duflo and Pande (2007) for dams and Asher and Novosad (2020) for village roads, both in India). We contribute to these literatures in three ways: first, our rich data allow us to characterize the optimal crop choice using the observed mean, variance, and covariance of yield shocks across crops; second, we demonstrate that rural bank access leads farmers to choose riskier crop portfolios; and third, we examine the interaction between rural bank access and domestic infrastructure policy.

The remainder of the paper is organized as follows. Section 2 describes the empirical context and the data we have assembled. Section 3 presents three new stylized facts relating trade to volatility. Section 4 introduces the baseline model, shows that it is consistent with the stylized facts, and analytically characterizes the second-moment welfare effects of trade. Section 5 structurally estimates an extended version of the model and quantifies these welfare effects. Section 6 concludes. Proofs, derivations, and additional theoretical results are contained in Appendix A, found in the Supplemental Material (Allen and Atkin (2022)). Additional details relating to the context, data and empirical exercises are contained in Online Appendix B, found in the replication file and on the authors' websites.

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 2009. This is a context in which the majority of households derive income from agriculture; 85% of the rural workforce was in agriculture in the 1971 Census and 72% in the 2011 Census. There were three major developments that had substantial impacts on the welfare of rural Indians over this period. First, increased use of irrigation and high-yield varieties (HYV) raised mean yields and altered the variance of yields. Second, policy-driven expansion of formal banking into rural areas helped farmers smooth income shocks and so

[3] Traders also play important roles in Allen (2014) and Chatterjee (2020); here, we abstract from information frictions and farmer-trader bargaining and instead focus on the role of volatility and its effect on farmers' crop choice.

provided a form of insurance. Online Appendix B.1.1 provides further details on these two developments.

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 changes. The first—which 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' (see Datta (2012), Ghani, Goswami, and Kerr (2016), Asturias, Garcia-Santana, and Ramos (2018) for impacts of these expansions on firm outcomes). 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% of total freight based on Indian government estimates. The second policy change was the broad economic liberalization program started in 1991 that gradually reduced agricultural tariffs both across states within India (see discussion in Atkin (2013)) and with the outside world. This paper focuses on domestic trade, that is, the inter-state and intra-state trade that constituted the overwhelming majority of India's agricultural trade over our sample period.

2.2. *Agricultural Trade in Rural India*

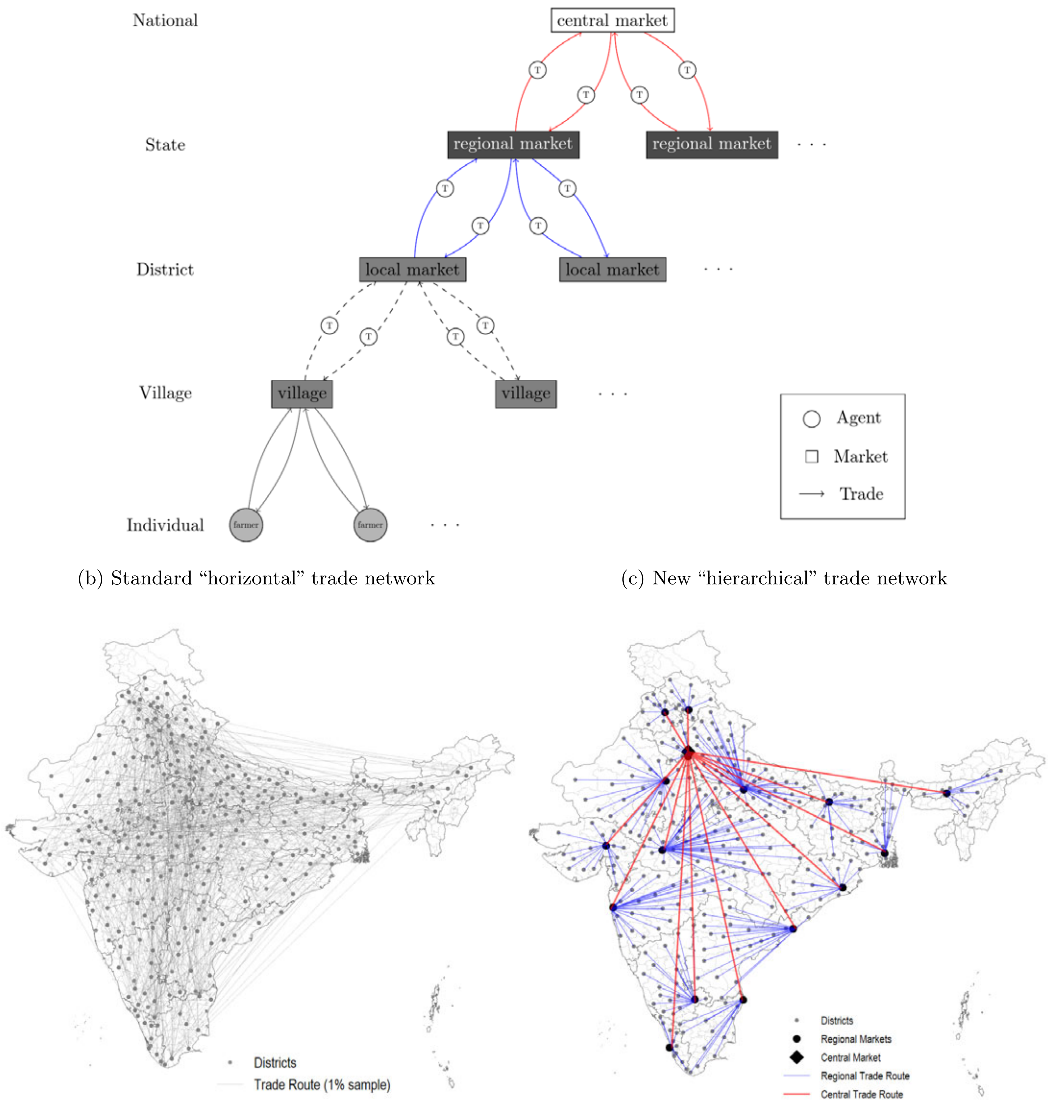
Agricultural trade in rural India has remained relatively unchanged since the 1960s, when the Agricultural Produce Marketing Committee (APMC) Acts were passed by Indian states. The APMC Acts established state-level marketing boards to regulate the trade of agricultural commodities, which in turn created state-regulated markets for agricultural trade called *mandis*—located in large towns near production centers—where farmers were legally required to sell their goods.

The basic structure of the trading process is as follows. Upon harvest, farmers either consume their produce directly or sell it to local traders in their village who transport it to the district mandi. At the mandi, the local traders sell the produce to (larger) regional traders who transport it to terminal markets in the state (or in some cases outside the state), which are typically located in large cities where the produce is processed for retail consumption. The result is a *hierarchical* trading network illustrated in panel (a) of Figure 1. Many farmers trade at the village level, many villages trade at the mandi level, many mandis trade at the state level, and many states trade at the national level, intermediated by traders at all but the bottom level. Unlike models where all locations trade directly with each other, our model below incorporates this more realistic hierarchical structure. Online Appendix B.1.2 provides further details on the mandi system.

In addition to the hierarchical trading structure, there are several other characteristics of agricultural trade in rural India that should be emphasized. First, these agricultural goods are best viewed as homogeneous. In each mandi, there is a market price for each type of good and that price exhibits very little variation across transactions on a given day.[4] Second, traders not only engage in arbitrage when purchasing farmers' production, they also engage in arbitrage when selling (potentially processed) agricultural goods for consumption.[5] Third, farmers take market prices as given, with traders earning any prof-

[4]For example, for mustard, paddy, and wheat where we observe daily mandi-level prices from 2006 onward, the median difference between the max and min price divided by the mode on a given day was 0.04, 0.06, and 0.07.

[5]The traders selling goods to farmers need not be the same individuals buying from farmers, although Chatterjee, Krishnamurthy, Kapur, and Bouton (2020) found that 39% of local traders in their sample also own village shops.



(a) The Indian agricultural trade network

(b) Standard "horizontal" trade network

(c) New "hierarchical" trade network

FIGURE 1.—A new (more realistic) model of the agricultural trade network. *Note*: This figure depicts the Indian agricultural trading network and compares it to the network assumed in a standard trade model and that assumed in our model. Panel (a) illustrates the actual structure of a typical Indian agricultural trading network. Panel (b) depicts the trading network of a standard trade model where each location can trade directly with all other locations (for readability, only a random 1% sample of links are shown). Panel (c) depicts the "hierarchical" trading network in our model, where each district only trades directly with a regional market, which in turn trades with a central market. Note panels (a) and (c) coincide except for the village-to-district trading links, which are excluded in the model due to the absence of village-level data.

its resulting from arbitrage (see Goyal (2010), Mitra, Mookherjee, Torero, and Visaria (2018), and Chatterjee (2020)). Fourth, traders exhibit a large degree of heterogeneity in their scale, varying from small traders who have no capital and incur large costs to transport goods (e.g., renting a tractor to carry produce to the mandi) to large multinational corporations. In our model below, we will incorporate each of these features: modeling goods as homogeneous (instead of as aggregates of a product with infinite varieties, as commonly assumed), having farmers take prices as given and traders earning profits (instead of perfect competition in the transport sector, as commonly assumed), and allowing traders to have heterogeneous trade costs (instead of homogeneous trade costs, as commonly assumed). Finally, we note that while the model developed below has been tailored to our empirical context, the characteristics above are common in agricultural settings throughout the developing world, suggesting its broader applicability.[6]

2.3. *Data*

We assemble the following data set on agricultural production and trade costs covering the entirety of the forty year period 1970–2009 (see Online Appendix B.2 for a more thorough data description):

Agricultural Data: Data on district-level cropping patterns (i.e., the area allocated), crop prices (the farm gate price a farmer receives), and crop yields come from the ICRISAT Village Dynamics in South Asia database (henceforth VDSA) which compiles various official government data sources. Cropping patterns, prices, and yields are all observed at the district $\times$ crop $\times$ year level for 311 districts (using time-invariant 1966 district and state boundaries) in 19 states that contain 95% of India's population. The database covers the 15 major crops (covering 73% of cropland) for which farm harvest prices are available. All Rupee values are deflated by the all-India CPI.

Trade Costs: We obtained all seven editions of the government-produced *Road Map of India* published between 1962 and 2011. We digitized and geo-coded these maps and identified the highways using an algorithm based on the color of digitized pixels. Figure 2 depicts the substantial expansion of the Indian highway 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. This image allows us to calculate travel times between any two districts using the Fast Marching Method (see Sethian (1999)), linearly interpolating to obtain years between editions.

Rural Bank Access: RBI bank openings by district come from Fulford (2013).

Consumer Preferences: Consumption data come from National Sample Survey (NSS) Surveys.

Rainfall Data: Gridded weather data come from Willmott and Matsuura (2012).

3. TRADE AND VOLATILITY: THREE STYLIZED FACTS

3.1. *Prices and Trade*

We first demonstrate the key mechanism linking trade and volatility. Online Appendix B.3 provides further estimation details (on all three stylized facts) and presents additional robustness exercises.

[6]For example, see Bergquist, McIntosh, and Startz (2021) on hierarchical trading networks in Uganda, Grant and Startz (2021) for chains of intermediation in Nigeria, Bergquist and Dinerstein (2020) and Dhingra and Tenreyro (2020) on imperfect competition among Kenyan agricultural traders, and Allen (2014) regarding heterogeneous agricultural traders in the Philippines.

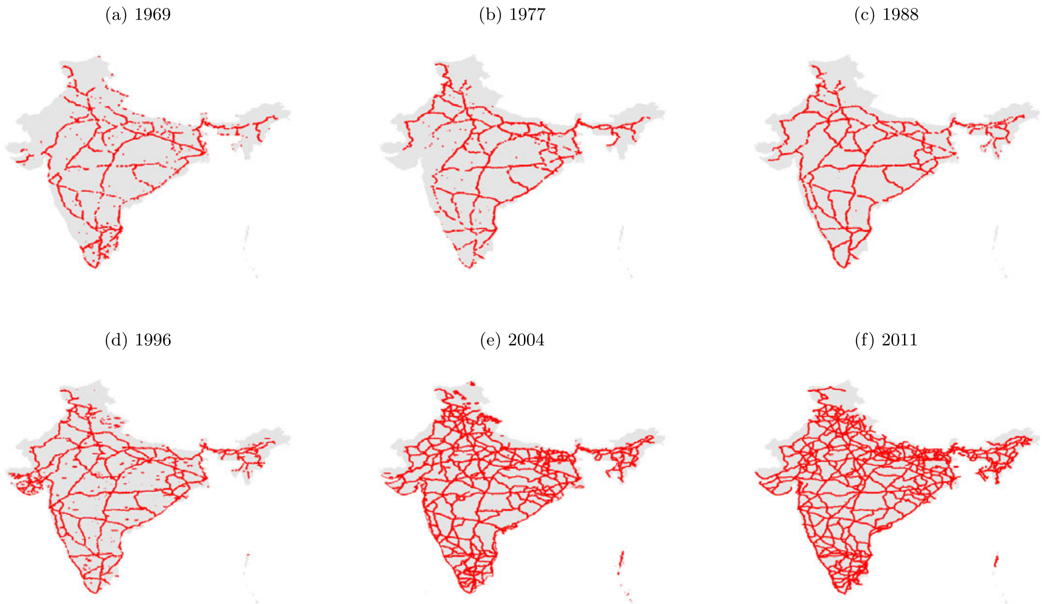


FIGURE 2.—The Indian highway network over time. *Note*: This figure shows the expansion of the Indian highway network over time. The networks are constructed by geocoding the scanned *Road Map of India* described in Section 2.3 for each of the above years and using image processing to identify the pixels 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.

Stylized Fact 1(a): As trade costs with other locations fall, prices respond less to local yields...

We first show that district-level prices are inversely related to district-level yield shocks, as a supply and demand model would predict, and that this responsiveness is attenuated as trade costs fall.

To do so, we regress district-level log prices on log yields and explore how the yield coefficient—the elasticity of price to yield—changes with reductions in the costs of trading with other locations:

$$\ln p_{igtd} = \beta_1 \ln A_{igtd} + \beta_2 \ln A_{igtd} \times \mathrm{MA}_{id}^{\mathrm{instate}} + \gamma_{gtd} + \gamma_{igd} + \gamma_{it} + \nu_{igdt}, \tag{1}$$

where $\ln p_{igtd}$ is the price in district i of good g in year t decade d, and $\ln A_{igtd}$ is the local yield. The variable $\mathrm{MA}_{id}^{\mathrm{instate}}$ captures district i's trade openness in decade d—as measured by market access to other districts in the state with the precise definition provided below. To control for confounds, we include three sets of fixed effects: a crop-year fixed effect γ_{gtd} that controls for changes in national or world prices of the good; a district-crop-decade fixed effect γ_{igd} that controls for slow-moving changes in crop-specific costs, in the area allocated to the crop, in preferences, or in technologies; and a district-year fixed effect γ_{it} that controls for local cost or demand shocks common to all crops (and sweeps out the level effect of market access). Finally, here and in the later facts, we make our results representative of rural India by weighting observations by the total area planted with our 15 crops in each district. We note that our specification, including the choice of fixed effects, will match the expression we derive for equilibrium prices in Section 4 below.

Our district-decade measure of openness derives from our digitized road maps. Motivated by the hierarchical structure of India's trading network described in Section 2.2, we consider within-state market access. (We explore the relevance of national market access below.) Following Donaldson and Hornbeck (2016), we construct a within-state market access measure for district i in year t by taking a weighted sum of the inverse bilateral travel times to other districts in i's state, the set S_i:

$$\mathrm{MA}_{it}^{\mathrm{instate}} = \sum_{j \in S_i} \left(\text{travel time}_{ijt}^{-\phi} Y_{jt}\right), \tag{2}$$

where Y_{jt} is district j's income in year t (proxied by total agricultural revenues) and $\phi > 0$ determines how quickly market access declines with travel time. Higher values of market access correspond to greater trade openness as districts are able to trade more cheaply with places where demand is high. Averaging district-year values within a decade provides us with our $\mathrm{MA}_{id}^{\mathrm{instate}}$ variable.[7]

To parameterize ϕ, we draw on the gravity literature that measures how rapidly log trade flows decline with log distance. Following meta-analyses, we set $\phi = 1.5$—the average gravity coefficient for developing country samples.[8] For robustness, we also consider $\phi = 1$, a natural benchmark and close to the average of 1.1 found when considering all countries, as well as alternate estimates of the off-highway speed of travel (1/4 of highway speed rather than 1/3).

Since farmers may invest more care harvesting crops that have high prices, yields may respond positively to price shocks, exerting an upward bias on the yield elasticity. To deal with this endogeneity concern, we instrument local yields with rainfall-predicted yields. Specifically, we regress log yields on local rainfall shocks in each month of that year interacted with state-crop fixed effects and include the same fixed effects as in the specification above. This generates a predicted yield measure that, after conditioning on the fixed effects, depends only on rainfall realizations and time-invariant parameters (and hence is unaffected by changes in the production technology over time). Predicted yields interacted with market access serve as our instrument for the interaction term. The instruments are very strong with a Kleibergen–Paap (KP) first-stage F-stat above 2000.

In order for the coefficients on the interaction between yield and market access to be interpreted causally, we further require that road building does not respond to changes in the elasticity of yields to prices after controlling for the rich set of fixed effects. Such endogeneity concerns are mitigated by the fact that much of the highway construction was part of centrally-planned national programs designed to connect larger regions. Reassuringly, changes in our market access measure are not associated with changes in relevant district characteristics such as bank access and HYV adoption; see Online Appendix B.3. To further address potential confounders, we interact yields with various sets of fixed effects below.

Columns 1 and 2 of Table I present the OLS and IV estimates of regression specification (1). As we would expect, a positive shock to supply lowers prices ($\beta_1 < 0$), with the

[7]We take decadal averages to align with the later stylized facts and with our quantitative analysis.

[8]Head and Mayer (2014) reported an average coefficient on log distance of −1.1 across 159 papers and 2508 regressions, while Disdier and Head (2008) reported that estimates from developing country samples are lower by an average of 0.44—consistent with distance being more costly in developing countries as found in Atkin and Donaldson (2015).

TABLE I

PRICE-YIELD ELASTICITIES AND OPENNESS.

	Log Price								
Dependent Variable:	(1) OLS	(2) IV	(3) IV	(4) IV	(5) RF	(6) RF	(7) IV	(8) IV	(9) IV
Log(Yield)	−0.033	−0.069	−0.071	−0.068			−0.082	−0.064	−0.080
	(0.004)	(0.010)	(0.012)	(0.010)			(0.015)	(0.016)	(0.020)
Log(Yield) × $MA^{instate}$	0.036	0.154					0.137	0.227	0.213
	(0.019)	(0.038)					(0.040)	(0.061)	(0.060)
Log(Yield) × $MA^{instate}$ (phi = 1)			0.067						
			(0.023)						
Log(Yield) × $MA^{instate}$ (alt. speed)				0.116					
				(0.033)					
$\text{Log}(\widehat{\text{Yield}})$ × $MA^{instate}$					0.070	0.246			
					(0.032)	(0.060)			
Log(Yield) × $MA^{outstate}$							0.035		0.048
							(0.033)		(0.034)
Log(StateYield)								−0.009	−0.001
								(0.013)	(0.012)
Log(StateYield) × $MA^{instate}$								−0.124	−0.131
								(0.052)	(0.052)
Log(NationalYield)									0.136
									(0.039)
Log(NationalYield) × $MA^{outstate}$									−0.103
									(0.054)
District-Crop-Decade FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Crop-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Crop-Decade Yield Interactions	No	No	No	No	Yes	No	No	No	No
Crop-District Yield Interactions	No	No	No	No	No	Yes	No	No	No
R-squared	0.946	0.001	0.001	0.001	0.946	0.950	0.000	0.001	0.001
Observations	86,811	86,811	86,811	86,811	86,811	86,811	86,811	86,172	86,172
First-Stage F-Stat	.	2449.4	2559.0	2442.9	.	.	1631.3	664.6	430.8

Note: Regressions of local log prices on local log yields and log yields interacted with within-state market access (i.e., access to districts in the same state). Each observation is a district-crop-year triplet. Column (1) reports OLS regression, while columns (2)–(4) and (7)–(9) report IV regressions instrumenting local yield terms with equivalents calculated with predicted yields and predicted yield equivalents interacted with market access. Predicted yield obtained from a regression of log yield on local rainfall shocks for each month interacted with state-crop fixed effects and controlling for district-crop-decade, crop-year, and district-year fixed effects. Columns (3) and (4) replace within-state market access with alternate within-state market access measures. Columns (5) and (6) report reduced form results that include crop-decade and crop-district interactions with predicted yields, respectively. Column (7) includes interactions with local log yields and outside-state market access (i.e., access to districts in other states). Columns (8) and (9) include additional interactions of within-state market access with state-level yields (i.e., cropped-area weighted averages of yields in other districts in the same state), and national-level market access with national yields (i.e., other states' cropped-area average yields). Observations are weighted by district-year total cropped area divided by the number of observations in a district year. Market access multiplied by 100,000. Robust standard errors reported in parentheses.

coefficient becoming more negative after instrumenting yields (consistent with the upward bias in the OLS discussed above). More central to our analysis, the elasticity of local prices to local yields increases significantly—from negative values toward zero—with improvements in market access. That is, as trade costs fall, the role that local prices play in insuring against yield shocks (i.e., prices rising when yields are low) is weakened. In terms of magnitudes, a rise in market access equal to the median 1970–2009 change in $MA_{id}^{instate}$ raises the elasticity by 0.017 (from a 1970s mean of −0.047).

These findings are robust to our two alternative market access measures (columns 3 and 4) and to controlling for crop-specific technological changes or differences in crop suitability across districts that are correlated with market access by interacting yields with fixed effects (columns 5 and 6).[9]

Finally, we explore whether the reduced responsiveness of prices to local yields also depends on changes in trade costs with locations outside the state. Column 7 supplements (1) with an interaction between local log yields and outside-state market access, $\mathrm{MA}_{id}^{\text{outstate}}$, calculated identically to $\mathrm{MA}_{id}^{\text{instate}}$ but now summing the inverse bilateral distances over all locations outside the state. The coefficient on the interaction is small and insignificant, consistent with restrictions on interstate commerce that motivate India's hierarchical trading network described in Section 2.2. The primacy of within-state market access will be echoed in all three stylized facts.[10]

Stylized Fact 1(b): ... and prices respond more to yields elsewhere

Reductions in trade costs also raise the responsiveness to yields in other districts. To demonstrate this, column 8 of Table I amends specification (1) to further include the log of the area-weighted average yields in the other districts within the same state, $\ln A_{-i,sgtd}$, as well as its interaction with within-state market access. Local prices decline with high yields elsewhere, with prices becoming significantly more responsive to yields elsewhere (i.e., decline more) with increases in market access.

3.2. *Crop Choices and Trade*

Our second set of stylized facts provides evidence that farmers respond to declines in trade costs by trading off traditional first-moment gains from specialization with second-moment risk reduction strategies, consistent with a portfolio choice model.

Stylized Fact 2(a): As trade costs fall, farmers reallocate their land toward crops for which they have a comparative advantage and away from crops that are more risky...

We first regress the share of land allocated to each crop on the mean and variance of yields of that crop, both interacted with our within-state market access measure $\mathrm{MA}_{id}^{\text{instate}}$ introduced above:

$$\begin{aligned}\operatorname{arcsinh}\theta_{igd} = {} & \beta_1\mu_{igd}^{A} + \beta_2\sigma_{igd}^{2,A} + \beta_3\mu_{igd}^{A}\times \mathrm{MA}_{id}^{\text{instate}} + \beta_4\sigma_{igd}^{2,A}\times \mathrm{MA}_{id}^{\text{instate}} \\ & + \gamma_{gd} + \gamma_{id} + \gamma_{ig} + \varepsilon_{igd},\end{aligned} \tag{3}$$

where $\operatorname{arcsinh}\theta_{igd}$ is the inverse hyperbolic sine of the decade-d average share of cropped land planted with crop g in district i, μ_{igd}^{A} is the mean of log yields in that district-crop-decade, and $\sigma_{igd}^{2,A}$ is the variance of log yields in that district-crop-decade (which, unlike the variance of yields, is mean-independent). We saturate the model by including crop-decade, district-decade, and district-crop fixed effects. These control for national crop-specific trends, district-decade level shocks, and persistent differences in local agroclimatic conditions that could potentially be related to local agricultural technologies and hence bias the β coefficients.

[9]Columns 5 and 6 include interactions with log yield and the full set of either crop-decade fixed effects or crop-district fixed effects. As discussed in Online Appendix B.3, we report reduced forms due to the large number of instruments.

[10]See column 9 of Table I, columns 5 and 8 of Table II, and columns 4–6 of Table III for these results.

As in Fact 1 above, our choice of specification—including the mean and variance of log yields as independent variables and the choice of fixed effects—arises directly from the expression we will derive for the equilibrium crop choice in Section 4. The one departure is the use of the inverse hyperbolic sine transformation in lieu of logging crop shares given that 19% of crop share observations in our regression sample are equal to zero.

To allay worries about endogenous movements in yields in response to cropping decisions—for example, cropping more marginal lands, which alters the mean and variance of yields—we instrument for the mean and variance of log yields with the same objects predicted from rainfall variation. Reassuringly, the instruments are strong with a KP first-stage F-stat of 117.

The OLS and IV regression coefficients are shown in columns 1 and 2 of Table II. The significant positive β_3 coefficient for both the OLS and IV implies that as trade costs fall—and hence market access improves—farmers respond by reallocating land toward crops in which they are relatively more productive. The significant negative β_4 coefficient indicates that a fall in trade costs also leads farmers to reallocate toward crops that have lower variances of yields. In terms of magnitudes, using the IV coefficients, a fall in trade costs equal to the median 1970–2009 change in within-state market access increases the responsiveness to mean log yields by one-fifth and changes the responsiveness of crop choice to the variance of log yields from a slightly positive one (coefficient 0.010) to a slightly negative one (coefficient -0.004). Similar results obtain when replacing yields (the exogenous variable in our theory) with the value of production in column 3.

Together, these results suggest that farmers are not only responding to trade cost declines by specializing in high yield crops in which they have a comparative advantage—the traditional "first-moment" effects—but also by reallocating land toward crops that are less risky—a "second-moment" effect of trade on risk mitigation that our portfolio allocation model below will emphasize.

Farmers may also engage in hedging and allocate more land to crops whose yields are less correlated with other crops in order to mitigate the increase in risk due to reductions in trade costs. To test this additional "second-moment" effect, we supplement equation (3) with $\sum_{g' \neq g} \sigma^A_{igg'd}$—the sum of the covariance of log yields of crop g with the log yields of each of the other 14 crops—and its interaction with market access. As a portfolio choice model would predict, column 4 of Table II shows a negative and significant coefficient on the interaction between the covariance term and market access (using rainfall-predicted covariances as instruments), with a magnitude similar to that on the variance interaction.

Stylized Fact 2(b): … with yield risk mattering more where risk mitigation technologies are worse

Fact 2(b) shows that the degree to which farmers trade off the first- and second-moment forces when choosing crop allocations depends on their access to risk mitigation technologies. As discussed in Section 2.1, local rural bank branches provide an important form of insurance as farmers can take out loans in bad times and repay them in good ones. We explore how this insurance technology affects crop choices by allowing bank access to affect the responsiveness of land allocations to the variance of yields.

TABLE II

CROP CHOICE AND OPENNESS.

	IHS fraction of land planted by crop							
Dependent Variable:	(1) OLS	(2) IV	(3) IV	(4) IV	(5) IV	(6) IV	(7) IV	(8) IV
Mean(log Yield)	0.001	0.004	−0.002	0.005	−0.006	0.002	0.002	−0.007
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)
Var(log Yield)	0.008	0.028	0.021	0.006	0.038	0.080	0.004	0.066
	(0.004)	(0.012)	(0.007)	(0.012)	(0.016)	(0.023)	(0.026)	(0.027)
Mean × $MA^{instate}$	0.012	0.010	0.015	0.010	0.001	0.012	0.012	0.003
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Var × $MA^{instate}$	−0.034	−0.125	−0.056	−0.074	−0.080	−0.224	−0.083	−0.174
	(0.016)	(0.031)	(0.014)	(0.034)	(0.028)	(0.062)	(0.075)	(0.058)
Covar(log Yield)				0.028			0.066	
				(0.009)			(0.020)	
Covar × $MA^{instate}$				−0.076			−0.133	
				(0.030)			(0.060)	
Mean × $MA^{outstate}$					0.021			0.022
					(0.005)			(0.005)
Var × $MA^{outstate}$					−0.044			0.002
					(0.026)			(0.044)
Var × Bank						−13.319	−3.019	−10.835
						(3.665)	(4.025)	(5.053)
Var × $MA^{instate}$ × Bank						22.719	7.370	16.277
						(8.327)	(9.956)	(7.709)
Covar × Bank							−8.646	
							(3.013)	
Covar × $MA^{instate}$ × Bank							13.646	
							(8.045)	
Var × $MA^{outstate}$ × Bank								−1.066
								(4.820)
Crop-Decade FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District-Decade FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District-Crop FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.972	−0.001	−0.000	−0.015	0.005	−0.006	−0.034	0.001
Observations	18,639	18,626	15,503	18,626	18,626	18,626	18,626	18,626
First-Stage F-Stat	.	117.1	216.0	37.7	84.3	78.6	14.8	22.9

Note: The dependent variable is the inverse hyperbolic sine of the fraction of land planted with a particular crop. Each observation is a district-crop-decade triplet. Columns (2)–(8) instrument for mean log yields and the variance of log yields with the mean and variance of log predicted yields from a regression of log yield on local rainfall shocks for each month interacted with state-crop fixed effects and controlling for crop-decade, district-decade, and district-crop fixed effects. Interactions with market access are instrumented with the predicted yield instruments interacted with market access. Columns (6)–(8) include additional interactions with district banks per capita. Column (3) replaces functions of yields with functions of the value of production, priced at state-average prices (and instrumented using functions of predicted yields multiplied by district-leave-out state prices). Columns (4) and (7) includes the sum of the covariance of yields with the other 14 crops plus interactions with within-state market access (instrumented with the covariance of predicted yields and interactions with within-state market access). Columns (5) and (8) repeat the interaction analysis with outside-state market access (i.e., access to districts in other states). Market access variables multiplied by 100,000 and banks per capita multiplied by 1000. Observations are weighted by the district-decade total cropped area divided by the number of observations in a district decade. Standard errors clustered at the district-decade level reported in parentheses.

Specifically, we extend specification (3) to include all interactions between the variance of log yields, market access, and bank access—measured as the decadal average of rural banks per capita in a district. Once again, we instrument the interaction terms with similar terms that replace the variance of log yields with the variance of log predicted yields.[11]

The estimates are shown in column 6 of Table II with the triple interaction positive and significantly different from zero at the 1% level. Consistent with farmers being willing to bear more risk if insured, the presence of more insurance options attenuates the movement into less risky crops that results from reductions in trade costs. That is, the better the bank access, the more important the "first-moment" effects of trade on specialization and the less important the "second-moment" effects of trade on risk mitigation. In terms of magnitudes, the increase in the responsiveness to the variance of yields that results from better market access shrinks by 40% when going from the 25th percentile of banks per capita to the 75th. Column 7 repeats this exercise with the covariance of log yields terms introduced in Fact 2(a). The triple interaction between the covariance of log yields, bank access, and market access is also positive and significant at the 10% level.

3.3. *Volatility and Trade*

Our third set of stylized facts captures the net impact of the mechanisms highlighted in Facts 1 and 2 by exploring the offsetting effects of reductions in trade costs on the volatility of income and the volatility of the price index.

Stylized Fact 3(a): As trade costs fall, farmers' revenue volatility increases...

First, we calculate nominal (gross) income—that is, the total revenue from the production of all 15 crops—using annual data on agricultural revenues per hectare. Of course, these are gross of crop costs which may change over time, an issue we confront head on in the structural estimation below.

To explore how the volatility of nominal income—that is, revenue volatility—responded to reductions in trade costs, for each district and decade we calculate $\text{var}(\ln \text{nominal income})_{id}$. We then project this object onto within-state market access:

$$\text{var}(\ln \text{nominal income})_{id} = \beta_1 \text{MA}_{id}^{\text{instate}} + \gamma_i + \gamma_{sd} + \varepsilon_{id}. \tag{4}$$

District fixed effects γ_i control for persistent differences in volatility, while state-decade fixed effects γ_{sd} control for temporal changes common to markets within a state. Note that here we are unable to exploit variation across crops within a district and time period as we did in Facts 1 and 2, making endogeneity concerns more substantial even with the inclusion of time trends at the lowest possible level, that is, state-decade. Thus, we should be more cautious in interpreting the following results as causal (and these concerns motivate the need for the quantitative results in Section 5 that isolate the effects of trade cost reductions alone). That said, it is reassuring that $\text{MA}_{id}^{\text{instate}}$ is uncorrelated with banks, yields, or yield-improving technologies; see Table B.1 in Online Appendix B.

Column 1 of Table III reports the estimated β_1 coefficient. Consistent with planting reallocations (Fact 2) only partially mitigating the reduced responsiveness of prices to yield shocks (Fact 1), the variance of log nominal income rises significantly with increases

[11]The first-stage F-stat remains strong (a value of 78.6). Endogenous bank placement may still induce a bias but, as discussed in Online Appendix B.3, it is reassuring that changes in market access and banks per capita are unrelated.

TABLE III

REAL INCOME AND OPENNESS.

	Components of Real Income					
Dependent Variable:	(1) Var Log Nominal Y	(2) Var Log P Index	(3) Var Log Real Y	(4) Var Log Nominal Y	(5) Var Log P Index	(6) Var Log Real Y
$MA^{instate}$	1.719	−0.475	1.062	1.858	−0.510	1.123
	(0.709)	(0.297)	(0.377)	(0.748)	(0.313)	(0.398)
$MA^{outstate}$				−0.473	0.117	−0.206
				(0.805)	(0.337)	(0.428)
District FE	Yes	Yes	Yes	Yes	Yes	Yes
State-Decade FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.542	0.755	0.489	0.542	0.755	0.489
Observations	1166	1166	1166	1166	1166	1166

Note: Regressions of the variance of the log of real income and its components on within-state market access (i.e., access to districts in the same state) multiplied by 100,000. Columns (4)–(6) additionally include outside-state market access (i.e., access to districts in other states) multiplied by 100,000. Each observation is a district-decade pair and includes all observations with at least 25% of cropped area with observed prices. Observations are weighted by district-decade total cropped area divided by the number of observations in a district decade. Robust standard errors reported in parentheses.

in market access. In terms of magnitudes, a rise in within-state market access equal to the median change in market access between the 1970s and 2000s increases the variance of log revenue by an amount equal to 78% of the mean 1970s variance. (The average variance rose 3.2-fold over this period with our reductions in trade costs accounting for 45% of this rise.)

Stylized Fact 3(b): … and the volatility of their price index declines…

To explore the impact of reductions in trade costs on the volatility of farmers' price indices, we construct for each district a Cobb–Douglas price index over the 15 crops in our sample.[12]

Column 2 of Table III replaces the dependent variable in (4) with $\text{var}(\ln \text{CD Price Index})_{id}$, the district-decade variance of the log Cobb–Douglas price index. Consistent with the reduced responsiveness of prices to yields documented in Fact 1—and in contrast to the rising volatility of nominal income—the coefficient on market access is negative. That is, the price index becomes less volatile with reductions in trade costs. While only about a third the size of the effect on revenue volatility, the coefficient is significantly different from zero with a p-value of 0.110.

Stylized Fact 3(c): … with the volatility of real income rising on net

Finally, we turn to impacts of reductions in trade costs on the variance of log real income, the ratio of log nominal income and the log Cobb–Douglas price index introduced above. Consistent with the observed rise in the volatility of nominal income coupled with a smaller decline in the volatility of the price index, column 3 of Table III shows that real

[12]We obtain district-level expenditure shares for each of these crops from the 1987 household-level NSS surveys and these (constant) shares serve as the weights in the Cobb–Douglas price index. Specifically, $\ln \text{CD Price Index}_{it} = \sum_g \text{bshare}_{ig} \ln p_{igt}$, where $\text{CD Price Index}_{it}$ is the Cobb–Douglas price index.

income volatility increases with within-state market access. The coefficient on market access falls by 38% compared to the nominal income specification, but the estimate is still positive and statistically significant.

To summarize, we have shown that falling trade costs reduce the responsiveness of prices to local yields but increase the responsiveness to yields elsewhere (Fact 1). Farmers respond by changing their crop allocations—trading off first-moment gains from specialization against second-moment strategies to mitigate risk (Fact 2)—but not enough to prevent increases in farmers' real income volatility (Fact 3). We now present a model that is sufficiently tractable to generate these comparative statics and sufficiently flexible to quantify the welfare impact of the Indian highway expansion.

4. MODELING TRADE AND VOLATILITY

In this section, we develop a new general equilibrium Ricardian model of trade and volatility. The model features farmers in many villages producing and consuming homogeneous crops and heterogeneous traders engaged in price arbitrage between villages and markets. In addition to mirroring our empirical context, the model yields tractable expressions for prices and patterns of specialization, allows us to incorporate volatility by applying tools from the portfolio choice literature, and yields predictions consistent with the three stylized facts above.

4.1. *Model Setup*

Geography. There are a large number of locations ("villages") indexed by $i \in \mathcal{N}$ and a central market. Each village i is inhabited by L_i identical farmers who produce and consume goods. The central market is inhabited by a set of heterogeneous traders who engage in an arbitrage process (described below) and drivers who are hired by the traders to ship goods between the central market and each of the villages.

Production. There are a finite number of homogeneous goods ("crops") indexed by $g \in \{1, \dots, G\} \equiv \mathcal{G}$ that can be produced in each location. Land is the only factor of production. Each farmer is endowed with a unit of land and chooses how to allocate that land across the production of each of the G crops. Let θ_{ig}^f denote the fraction of land farmer f living in village i allocates to good g, where $\sum_{g \in \mathcal{G}} \theta_{ig}^f = 1$; we refer to $\{\theta_{ig}^f\}_{g \in \mathcal{G}}$ as farmer f's *crop choice*.

Production is risky. Let the (exogenous) yield of a unit of land in location i for good g be $A_{ig}(s)$, where $s \in S$ is the state of the world. Given her crop choice, farmer f receives nominal income $Y_i^f(s) = \sum_{g \in \mathcal{G}} \theta_{ig}^f A_{ig}(s) p_{ig}(s)$ in state s, where $p_{ig}(s)$ is the price of good g in location i.

While we abstract from idiosyncratic risk in this setup, an alternative (mathematically equivalent) interpretation is that farmers face idiosyncratic risk but engage in perfect risk-sharing arrangements with other farmers in the same location. Consistent with this interpretation, Table B.6 in Online Appendix B echoes the seminal work of Townsend (1994) by showing that across four NSS survey rounds spanning 1987–2005, household consumption is more responsive to district-level rainfall-induced income shocks than to the same shocks at the household level.

Preferences. Farmers have constant relative risk aversion preferences with an *effective risk aversion* parameter $\rho_i > 0$:

$$U_i^f(s) \equiv \frac{1}{1-\rho_i}\left(\left(Z_i^f(s)\right)^{1-\rho_i} - 1\right), \tag{5}$$

where $Z_i^f(s) \equiv \prod_{g\in\mathcal{G}} c_{ig}^f(s)^{\alpha_{ig}}$ is a Cobb–Douglas aggregate of goods, $c_{ig}^f(s)$ denotes the quantity consumed of good g in state s, and $\alpha_{ig} > 0$ is the expenditure share spent on good g with $\sum_{g\in\mathcal{G}} \alpha_{ig} = 1$. As $Z_i^f(s)$ can be written in its indirect utility form as nominal income divided by a price index, in what follows we refer to $Z_i^f(s)$ as a farmer's *real income*. Traders and drivers are assumed to have the same Cobb–Douglas preferences over goods.

Following Eswaran and Kotwal (1990), we refer to ρ_i as the *effective risk aversion* and interpret it as combining both the innate risk preferences of the farmer and any access the farmer has to ex post risk mitigating technologies (savings, borrowing, insurance, etc.). In Appendix A.3.3, we micro-found this interpretation by allowing farmers to purchase insurance from perfectly competitive local money-lenders ("banks"). In the spirit of this interpretation, Table B.6 in Online Appendix B extends the Townsend-like exercise above and shows that as local bank access improves, the responsiveness of household consumption to household shocks shrinks and the response to district shocks rises.

Trade. A large number of traders arbitrage prices across locations subject to (ad valorem) trade costs. We assume that traders are heterogeneous in their trading technology and capacity constrained.[13] As a result of this heterogeneity, the standard no-arbitrage equation—that the trade costs bound the price ratio—is replaced by an alternative condition (equation (9) below) that has the intuitive property that more goods flow toward a destination when its relative price is higher.

We now describe the trading process that delivers this key arbitrage equation. However, our results hold for any process that micro-founds this equation. For example, Appendix A.3.4 shows it also arises from iceberg trade costs that are increasing and convex in the quantity shipped.

Every farmer wishing to buy or sell is randomly matched to a trader. If a farmer wishes to sell a unit of good g, the trader she is matched to pays her the local market price $p_{ig}(s)$ and then decides whether to sell it locally or export it to the central market. If the trader decides to sell the good locally, he sells it for $p_{ig}(s)$, making zero profit. If the trader exports the good, he sells it for the central market price $\bar{p}_g(s)$, incurs an (iceberg) trade cost τ_{ig}, and earns profit $\bar{p}_g(s) - \tau_{ig} p_{ig}(s)$.[14]

The process works in reverse for a farmer wishing to buy some quantity of good g. She is randomly matched to a trader and buys for the local price $p_{ig}(s)$. The trader previously decided whether to import the good from the central market (paying $\bar{p}_g(s)$ but incurring

[13] The assumption that traders are capacity constrained is made only for convenience: Appendix A.3.1 shows that a model where better traders can offer greater capacity is isomorphic to the model presented here.

[14] We assume the trade cost is a transfer paid to agents ("drivers") that, along with traders, inhabit the central market and for whom moving goods provides all their income. By assuming drivers have no other income, we abstract from the gains from trade arising from the direct reduction of resources necessary to move goods, instead focusing on gains arising from comparative advantage and specialization. In what follows, we present combined welfare results for all residents of the central market; Appendix A.3.2 provides separate expressions for trader and driver income.

iceberg trade cost τ, for a profit of $p_{ig}(s) - \tau_{ig}\bar{p}_g(s)$) or to source it locally (paying $p_{ig}(s)$, earning zero profit).

Trade costs τ_{ig} to ship good g between village i and the central market (in either direction) are heterogeneous across traders and drawn from a Pareto distribution with shape parameter $\varepsilon_i \in (0, \infty)$:

$$\Pr\{\tau_{ig} \leq \bar{\tau}\} = 1 - \bar{\tau}^{-\varepsilon_i}. \tag{6}$$

The greater the value of ε_i, the lower the average trade costs between the village and central market (as $\varepsilon_i \to 0$, trade becomes infinitely costly, and as $\varepsilon_i \to \infty$, trade becomes costless for all traders).

Discussion. We draw three distinctions between this setup and agricultural trade models based on the canonical framework of Eaton and Kortum (2002) (e.g., Donaldson (2018), Costinot, Donaldson, and Smith (2016), Sotelo (2020), and Bergquist et al. (2019)). First, unlike in Eaton and Kortum (2002) where tractability arises from assuming that each location draws different productivities for each of a continuum of varieties of a crop (with Fréchet distributed draws), here, tractability arises from trade costs being heterogeneous across traders (with Pareto distributed draws). Second, unlike in Eaton and Kortum (2002) where every location trades directly with every other location (as in panel (b) of Figure 1), here, trade between villages occurs only indirectly through the traders in a central market. Third, unlike in Eaton and Kortum (2002) where buyers alone engage in price arbitrage by choosing the seller offering the lowest price, here, traders engage in price arbitrage both when buying from farmers and when selling to them. Each of these distinctions serves to more closely match the reality of agricultural trade in India described in Section 2.2.

4.2. *Trade and Prices*

We begin by characterizing equilibrium trade and prices.

Villages. Consider first a trader selling produce to a farmer and deciding from where to source the good. If the village price is lower than the central market price, that is, $p_{ig}(s) \leq \bar{p}_g(s)$, then no arbitrage opportunity exists and all traders will source the good locally. But if the central market price is lower than the local price, $p_{ig}(s) > \bar{p}_g(s)$, some traders will engage in price arbitrage, buying in the central market and selling for a profit in the village.

Now consider a trader buying produce from a farmer and deciding where to sell it. If the village price is greater than the central market price, $p_{ig}(s) \geq \bar{p}_g(s)$, then no arbitrage opportunity exists and all traders will sell the good locally. But if the central market price is greater than the village price, $\bar{p}_g(s) > p_{ig}(s)$, then some traders will engage in price arbitrage, buying in the village and selling for a profit in the central market.

Thus, for the market of good g in village i to clear when $p_{ig}(s) > \bar{p}_g(s)$, that is, when good g is flowing into the village, it must be the case that the quantity produced by the village is equal to the total quantity consumed locally multiplied by the probability that traders source from the village:

$$C_{ig} \times \Pr\{p_{ig}(s) \leq \tau_{ig}\bar{p}_g(s)\} = Q_{ig}. \tag{7}$$

For the market of good g in village i to clear when $p_{ig}(s) < \bar{p}_g(s)$, that is, when good g is flowing out of the village, it must be the case that the quantity consumed locally is equal to the total quantity produced locally multiplied by the probability that the traders sell to the village:

$$Q_{ig} \times \Pr\{\tau_{ig} p_{ig}(s) \geq \bar{p}_g(s)\} = C_{ig}. \tag{8}$$

Combining equations (7) and (8) with the Pareto distribution of trade costs from (6), we immediately see that—regardless of the relative prices and hence regardless the direction of trade—the relationship between relative prices and quantities consumed and produced can be written as

$$C_{ig}(s) = \left(\frac{p_{ig}(s)}{\bar{p}_g(s)}\right)^{\varepsilon_i} Q_{ig}(s). \tag{9}$$

Intuitively, equation (9) states that trader arbitrage results in the good flowing toward locations with higher relative prices with an elasticity governed by the distribution of trade costs ε_i.

Combining equation (9) with the farmers' Cobb–Douglas demand, we obtain

$$\ln p_{ig}(s) = -\left(\frac{1}{1+\varepsilon_i}\right) \ln Q_{ig}(s) + \left(\frac{\varepsilon_i}{1+\varepsilon_i}\right) \ln \bar{p}_g(s) + \left(\frac{1}{1+\varepsilon_i}\right) \ln\bigl(\alpha_{ig} Y_i(s)\bigr). \tag{10}$$

Equation (10) shows how a village's openness (summarized by its Pareto shape parameter ε_i) determines how its own production affects its equilibrium prices. In autarky ($\varepsilon_i = 0$), the price elasticity is 1, consistent with the Cobb–Douglas demand. But as trade costs fall (ε_i increases), the elasticity of prices to own quantity produced falls, with the elasticity tending to zero as trade becomes costless ($\varepsilon_i \to \infty$). This fall in the elasticity of local prices to local production occurs simultaneously with an increase in the elasticity of local prices to the prices in the central market.

It is useful to contrast this relationship between prices and quantity with the relationship in a model in which trade costs are assumed to be homogeneous: In such a model, local prices equal autarky village prices as long as the absolute price gap between the autarky village price and the central market price is less than or equal to the costs of trading. But whenever the price gap exceeds this value, traders engage in arbitrage and the local price is pinned down by the central market price net of trade costs. This results in a "kinked" demand curve—illustrated in panel (a) of Figure 3. In our model—illustrated in panel (b) of Figure 3—there are no such kinks in the demand curve; instead, trader heterogeneity ensures a smooth relationship (log linear given the Pareto assumption) between prices and quantities. In panel (c) of Figure 3, we compare the two arbitrage models' abilities to explain the observed relationship between prices and (rainfall-predicted) quantities (see Appendix A.4 for details). The "smooth" model substantially outperforms the more-standard "kinked" model, explaining a larger fraction of the observed variation with an average R^2 of 0.15 (versus 0.11 in a "kinked" model) across district-decades.

Central Market. The quantity consumed in the central market is equal to the total net inflows of goods from each village:

$$\bar{C}_g(s) = \sum_{i \in \mathcal{N}} \left(1 - \left(\frac{p_{ig}(s)}{\bar{p}_g(s)}\right)^{\varepsilon_i}\right) Q_{ig}(s), \tag{11}$$

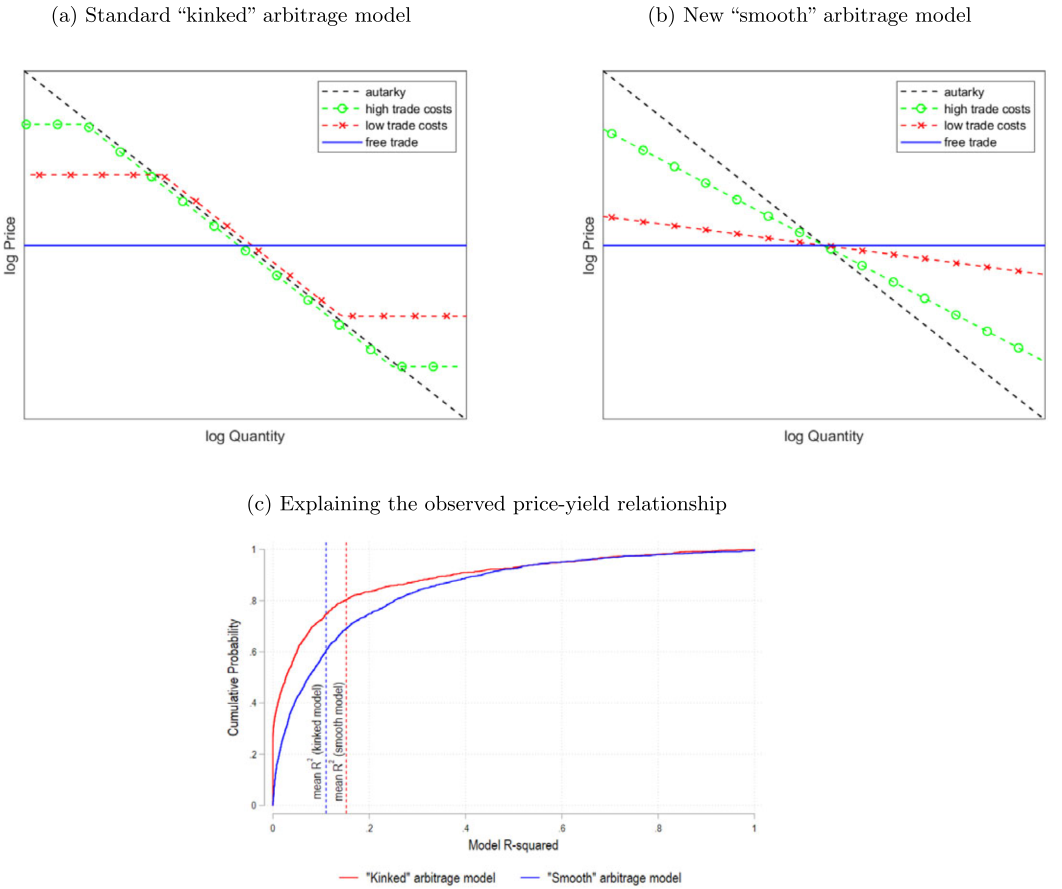


FIGURE 3.—A new (more realistic) model of price arbitrage. *Note*: This figure compares our model to a standard model of price arbitrage. Panel (a) depicts the "kinked" relationship between local prices and local quantities produced in a standard trade model, where (log) local prices are equal to the (log) world price plus/minus an iceberg trade cost other than in a narrow range where relative prices are sufficiently similar that no trade occurs and prices are determined by autarkic demand. Panel (b) depicts the "smooth" relationship between local prices and local quantities in our model, where heterogeneous trade costs ensure that some trade occurs at all prices, and the distribution of trade costs across traders determines the elasticity of local prices to local quantities produced. Panel (c) compares the fit of the two models to Indian data on rainfall-predicted quantities and observed yields and reports the distribution of R^2 for each model across all district-decade pairs in our sample; see Section 4.2 for details.

and the income of central market residents (i.e., traders and drivers) is equal to the total arbitrage revenues earned across all crops and villages:

$$\bar{Y}(s) = \sum_{g \in \mathcal{G}} \sum_{i \in \mathcal{N}} \left(\bar{p}_g(s) - p_{ig}(s)\right)\left(1 - \left(\frac{p_{ig}(s)}{\bar{p}_g(s)}\right)^{\varepsilon_i}\right) Q_{ig}(s). \tag{12}$$

Combining the arbitrage equation (10) with equations (11) and (12), and imposing the Cobb–Douglas demands of central market residents, one can calculate the equilibrium prices in the central market, and hence each village via equation (10). Formally, the following definition holds.

DEFINITION 1: Given any set of preferences $\{\alpha_{ig}\}_{i\in\mathcal{N}}^{g\in\mathcal{G}}$, trade costs $\{\varepsilon_i\}_{i\in\mathcal{N}}$, the population distribution $\{L_i\}_{i\in\mathcal{N}}$, and any state of the world $s\in S$ such that quantity produced is $\{Q_{ig}(s)\}_{i\in\mathcal{N}}^{g\in\mathcal{G}}$, a *state equilibrium* is a set of village prices $\{p_{ig}(s)\}_{i\in\mathcal{N}}^{g\in\mathcal{G}}$, village consumption $\{C_{ig}(s)\}_{i\in\mathcal{N}}^{g\in\mathcal{G}}$, central market prices $\{\bar{p}_g(s)\}_{g\in\mathcal{G}}$, and central market consumption $\{\bar{C}_g(s)\}_{g\in\mathcal{G}}$ such that:

1. Markets clear within each village, that is, (a) farmers' income equals the value of their produce; (b) farmers maximize utility given their income; and (c) traders optimally engage in arbitrage.
2. Markets clear within the central market, that is, (a) traders' and drivers' combined income is equal to arbitrage revenue; and (b) central market prices equate demand and supply.

The following proposition shows that the equilibrium is well defined.

PROPOSITION 1: *Given any set of preferences $\{\alpha_{ig}\}_{i\in\mathcal{N}}^{g\in\mathcal{G}}$, trade costs $\{\varepsilon_i\}_{i\in\mathcal{N}}$, and any state of the world $s\in S$ such that quantity produced is $\{Q_{ig}(s)\}_{i\in\mathcal{N}}^{g\in\mathcal{G}}$:*

1. *There exists a state equilibrium.*
2. *If the trade costs $\{\varepsilon_i\}_{i\in\mathcal{N}}$ are sufficiently close to* 1, *then that equilibrium is unique.*

PROOF: See Appendix A.2.1. *Q.E.D.*

Part 1 of Proposition 1 shows that the equilibrium is well defined for any geography of trade costs and realized quantities produced. Part 2 provides sufficient conditions for uniqueness by establishing conditions under which the excess demand function satisfies the gross substitutes property. As gross substitutes is itself a sufficient but not necessary condition, we expect uniqueness is a more general phenomenon; consistent with this conjecture, an iterative algorithm based on equation (11) converges rapidly to an equilibrium for a wide variety of $\{\varepsilon_i\}$; see Online Appendix B.5 for details.

4.3. *Optimal Crop Choice*

We now derive a convenient expression showing how trade affects farmers' optimal crop choice. To provide intuition, we first consider the special case where production is not volatile.

No Volatility. In the absence of volatility, and taking prices as given, a farmer will equalize her income per unit of land (i.e., her factor price) across all goods she produces:[15]

$$p_{ig}A_{ig}=\lambda_i\quad\forall g\in\{1,\dots,G\},\tag{13}$$

where $\lambda_i>0$ is the shadow value of land. Substituting in the equilibrium price from equation (10), imposing symmetry across farmers so that $\theta_{ig}^f=\theta_{ig}$ for all farmers f in village i, and applying the constraint that land shares sum to 1 yields

$$\theta_{ig}=\frac{\alpha_{ig}(A_{ig}\bar{p}_g)^{\varepsilon_i}}{\sum_{h\in\mathcal{G}}\alpha_{ih}(A_{ih}\bar{p}_h)^{\varepsilon_i}}.\tag{14}$$

[15] In equilibrium, all goods will be produced in all locations as equation (10) implies that the price of a good will become infinite as the land allocated to that good tends to zero.

Farmers specialize more in the production of good g the greater their own demand for that good (α_{ig}) and the greater the market returns from producing that good ($A_{ig}\bar{p}_g$), with the relative weights of the two considerations depending on the degree of openness to trade (ε_i). As a village becomes more open (i.e., ε_i increases), farmers allocate a greater fraction of their land toward goods that have high market returns rather than toward goods they wish to consume.

What about the gains from trade? It turns out that in the absence of volatility, farmers' welfare does not depend on the degree of openness. 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 grow more of those crops. Unlike a standard Ricardian trade model, however, local prices fall as more comparative advantage crops are grown since not all of the excess production is exported by the heterogeneous traders. Farmers continue to reallocate toward their comparative advantage crops up to the point that their returns per unit land are equalized across crops, resulting in the same autarkic relative prices and thus leaving their welfare unchanged.[16] This is not to say that there are no gains from specialization; there are. But these gains are captured entirely by the traders engaging in price arbitrage—a model feature that we believe is realistic given the large literature referenced in the introduction documenting the substantial market power traders have over small farmers. This result also helps isolate the source of farmers' gains from trade in a world with volatility.

Volatility. We now turn to the more general case where productivity is volatile, due for example to variation in rainfall. Farmers now equalize their marginal expected utility (rather than marginal nominal income) across crops, necessitating a characterization of the distribution of farmers' real income over all states of the world. To do so, we combine techniques from the portfolio choice literature in finance with the general equilibrium trade framework above. This general equilibrium structure adds substantial complication to the problem since the distribution of farmers' real incomes depends on the geography of trade costs, the distribution of yields, and the crop choices of all other farmers. Despite this complexity, however, we are still able to derive an explicit expression for farmers' equilibrium crop choice that is a straightforward generalization of equation (14).

We begin by positing the following distribution of crop yields across states of the world:

ASSUMPTION 1—Log-normal distribution of yields: *Assume that the joint distributions of yields across goods are log-normal within village i and are independently distributed across villages. In particular, define* $\mathbf{A}_i(s)$ *as the* $G \times 1$ *vector of* $A_{ig}(s)$. *Then* $\ln \mathbf{A}_i \sim N(\boldsymbol{\mu}^{A,i}, \boldsymbol{\Sigma}^{A,i})$ *for all* $i \in \{1, \dots, N\}$, *where* $\boldsymbol{\mu}^{A,i} \equiv [\mu_g^{A,i}]$ *is a* $G \times 1$ *vector and* $\boldsymbol{\Sigma}^{A,i} \equiv [\Sigma_{gh}^{A,i}]$ *is a* $G \times G$ *variance-covariance matrix.*

That yield realizations are independently distributed across many locations implies that the (endogenous) central market price is state invariant, that is, shocks to yields in individual villages "average out" in the aggregate. While helpful for simplifying the exposition, we relax this independence assumption in the quantification in Section 5 by allowing yield shocks to be correlated across villages and central market prices to be state dependent.

[16] A crucial assumption underlying this result is that each farmer takes the market prices as given. If, instead, farmers internalized the effect of their crop allocation choice on equilibrium prices, say through the formation of an agricultural collective, they would choose to restrict the degree to which they specialize, increasing the price of their comparative advantage goods and improving their terms of trade. See Appendix A.3.5 for further details.

We next follow the finance literature (see, e.g., Campbell and Viceira (2002)) and approximate the real income of farmer f by taking a second-order approximation around its (log) mean (see Appendix A.1 for derivations of this and later expressions in this section):[17]

$$\ln Z_i^f(s) \approx \mu_i^Z + \sum_{g\in\mathcal{G}}\left(\left(\frac{\varepsilon_i}{1+\varepsilon_i}\right)\theta_{i,g}^f + \left(\frac{1}{1+\varepsilon_i}\right)\alpha_{ig}\right)\left(\ln A_{ig}(s) - \mu_g^{A,i}\right), \tag{15}$$

where μ_i^Z—defined in Appendix A equation (28)—is a scalar that depends on crop choice and equilibrium market prices, but not on the particular state of the world s. Equation (15) states that the more open a village is (i.e., the higher ε_i), the more a farmer is engaged with buying and selling goods in the market, and the more a farmer's real income depends on the realized local yield shocks ($\ln A_{ig}(s) - \mu_g^{A,i}$) of the crops she grows ($\theta_{i,g}^f$) than on the yields of the crops she consumes (α_{ig}).

Next, we calculate the expected utility of farmers as a function of their crop choice (and the crop choices of all other farmers). From equation (15), it immediately follows that farmer real income is (approximately) log-normally distributed across states of the world, that is, $\ln Z_i^f \sim N(\mu_i^Z, \sigma_i^{2,Z})$, where the variance of her log real income $\sigma_i^{2,Z}$—defined in Appendix A equation (29)—depends on her equilibrium crop choice. This in turn implies that expected utility takes a convenient form:

$$\mathbb{E}\left[U_i^f\right] = \frac{1}{1-\rho_i}\left(\exp\left((1-\rho_i)\left(\ln \mathbb{E}\left(Z_i^f\right) - \rho_i\sigma_i^{2,Z}\right)\right) - 1\right), \tag{16}$$

where $\mathbb{E}(Z_i^f) = \exp(\mu_i^Z + \frac{1}{2}\sigma_i^{2,Z})$ since Z_i^f is log-normally distributed. Thus, 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 effective risk aversion ρ_i.

The first-order conditions of the farmer's crop choice problem then imply that the marginal contribution of each crop to expected utility should be equalized:

$$\mu_{ig}^Z - \rho_i\left(\frac{\varepsilon_i}{1+\varepsilon_i}\right)\sum_{h\in\mathcal{G}}\left(\left(\frac{\varepsilon_i}{1+\varepsilon_i}\right)\theta_{i,h}^f + \left(\frac{1}{1+\varepsilon_i}\right)\alpha_{ih}\right)\Sigma_{gh}^{A,i} = \lambda_i, \tag{17}$$

where $\mu_{ig}^Z \equiv \frac{\partial \ln \mathbb{E}(Z_i^f)}{\partial \theta_{ig}^f}$ is the marginal contribution of crop g to the log of the mean real income and λ_i is the shadow value of land. Equation (17)—which generalizes the indifference condition (13) to accommodate volatility—is intuitive: a good with a higher marginal contribution to the variance of real returns must have higher marginal contribution to the mean real returns (i.e., a high μ_{ig}^Z) to compensate for the additional risk. This expression will prove essential when estimating farmers' effective risk aversion from their observed crop choices in Section 5.2 below.

Finally, by combining farmers' first-order conditions (17), imposing symmetry across farmers within village, and imposing that crop shares sum to 1, we can derive an expression for the equilibrium crop choice that generalizes equation (14) to incorporate

[17]The second-order approximation implies that the sum of log-normal variables is itself approximately log-normal. Campbell and Viceira (2002) approximated around zero returns which is valid over short horizons; because our time period is a year, we approximate around the mean log yields. In the quantitative results in Section 5.3 below, we find that the approximated expected utility is highly correlated (exceeding 0.999) with the actual expected utility.

volatility:

$$\theta_{ig} = \frac{\alpha_{ig}(B_{ig}\bar{p}_g)^{\varepsilon_i}}{\sum_{h\in\mathcal{G}} \alpha_{ih}(B_{ih}\bar{p}_h)^{\varepsilon_i}}, \tag{18}$$

where B_{ig} is the *risk adjusted productivity* of farmers in location i producing crop g.[18] In the absence of volatility, the risk adjusted productivity is simply the actual productivity, that is, $B_{ig} = A_{ig}$, and equation (18) collapses to (14). But in the presence of volatility (and for sufficiently high risk aversion ρ_i), B_{ig} is smaller the greater g's marginal contribution to the aggregate volatility of real returns, so that farmers trade off traditional "first-moment" benefits from specializing in crops with higher mean yields against "second-moment" benefits of specializing in less risky crops.

4.4. *Characterizing the Equilibrium of the Model*

We now define an equilibrium and characterize its properties.

DEFINITION 2: Given any set of preferences $\{\alpha_{ig}\}_{i\in\mathcal{N}}^{g\in\mathcal{G}}$, trade costs $\{\varepsilon_i\}_{i\in\mathcal{N}}$, and distributions of yields across states of the world $\{\boldsymbol{\mu}^{A,i}, \boldsymbol{\Sigma}^{A,i}\}_{i\in\mathcal{N}}$, an *equilibrium* is a set of crop allocations $\{\theta_{ig}\}_{i\in\mathcal{N}}^{g\in\mathcal{G}}$ and, for each state of the world $s \in S$, a set of village prices $\{p_{ig}(s)\}_{i\in\mathcal{N}}^{g\in\mathcal{G}}$, village consumption $\{C_{ig}(s)\}_{i\in\mathcal{N}}^{g\in\mathcal{G}}$, central market prices $\{\bar{p}_g(s)\}_{g\in\mathcal{G}}$, and central market consumption $\{\bar{C}_g(s)\}_{g\in\mathcal{G}}$ such that:
1. Each state of the world $s \in S$ is in a state equilibrium.
2. Farmers optimally choose their crop allocation to maximize their expected utility across all states, that is, crop choice satisfies equation (18).

Because Proposition 1 holds for any realized quantities produced $\{Q_{ig}(s)\}_{i\in\mathcal{N}}^{g\in\mathcal{G}}$, including those that would arise from the optimal crop allocation, it immediately implies the following corollary:

COROLLARY 1: *For any set of preferences* $\{\alpha_{ig}\}_{i\in\mathcal{N}}^{g\in\mathcal{G}}$, *trade costs* $\{\varepsilon_i\}_{i\in\mathcal{N}}$, *and distributions of yields across states of the world* $\{\boldsymbol{\mu}^{A,i}, \boldsymbol{\Sigma}^{A,i}\}_{i\in\mathcal{N}}$, *there exists an equilibrium and it is unique if each* $\{\varepsilon_i\}_{i\in\mathcal{N}}$ *is sufficiently close to* 1.

Having characterized the equilibrium of the model, we now turn to its qualitative implications.

4.5. *Qualitative Implications*

Explaining the Stylized Facts. The model generates the stylized facts in Section 3:

PROPOSITION 2: *Consider a small increase in village i's openness to trade* ε_i:
(a) [*Stylized Fact* 1] *Any increase in openness*: (1a) *decreases the responsiveness of local prices to local yield shocks*; *and* (1b) *increases the responsiveness of local prices to the central market price*.

[18] Specifically, $B_{ig} \equiv \exp(\mu_g^{A,i})/(\lambda_i - (\frac{1}{2}(\frac{\varepsilon_i}{1+\varepsilon_i})^2\Sigma_{gg}^{A,i} + \frac{\varepsilon_i}{(1+\varepsilon_i)^2}\sum_{h\in\mathcal{G}}\alpha_{ih}\Sigma_{gh}^{A,i} - \rho_i(\frac{\varepsilon_i}{1+\varepsilon_i})\sum_{h\in\mathcal{G}}((\frac{\varepsilon_i}{1+\varepsilon_i})\theta_{i,h} + (\frac{1}{1+\varepsilon_i})\alpha_{ih})\Sigma_{gh}^{A,i}))$.

(b) [*Stylized Fact* 2] *Starting from autarky*, *any increase in openness*: (2a) *causes farmers to reallocate production toward crops with higher mean and less volatile yields* (*as long as* $\rho_i > 1$, *i.e.*, *farmers are sufficiently risk averse*); *and* (2b) *the reallocation toward less volatile crops is attenuated the greater the access to insurance* (*i.e.*, *the lower* ρ_i).

(c) [*Stylized Fact* 3] *Any increase in openness*: (3a) *increases farmers' nominal income volatility*; (3b) *decreases farmers' nominal price volatility*; *and* (3c) *has an ambiguous effect on farmers' real income volatility*.

PROOF: See Appendix A.2.2 for the mathematical statements and proofs. *Q.E.D.*

As trade costs fall and a village becomes more open, more traders engage in arbitrage, which reduces the responsiveness of prices to local yields and increases the responsiveness of local prices to the central market price—consistent with Stylized Fact 1. Farmers react to the increase in openness by changing their crop allocation, placing less weight on crops they consume and more weight on those in which they have a comparative advantage. But at the same time, to mitigate the increased risk farmers now face due to local prices being less responsive to local yields, farmers respond by moving into crops with less volatile yields. The trade-off between these traditional "first-moment" gains from specialization and "second-moment" efforts to reduce risk is governed by their level of risk aversion—consistent with Stylized Fact 2. Because prices become less responsive to local yields, farmers face more volatile nominal incomes at the same time as more stable consumption prices—consistent with Stylized Fact 3, with the net effect on the volatility of real income depending on the extent to which a farmer's crop allocation is more risky than her expenditure allocation.

Volatility and the Gains From Trade. We now turn to the welfare implications of the model. We summarize the relationship between welfare, trade costs, and volatility in the following proposition:

PROPOSITION 3: (1) *In the presence of volatility*, *moving from autarky to costly trade improves farmer welfare*, *that is*, *the gains from trade are positive*; (2) *moving from a world with no volatility to one with volatility amplifies farmers' gains from trade*; *but* (3) *increasing the volatility in an already volatile world may attenuate farmers' gains from trade*.

PROOF: See Appendix A.2.3. *Q.E.D.*

Part (1) of Proposition 3 arises from a standard revealed preference argument (see, e.g., Dixit and Norman (1980)). Because all farmers in a location 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, 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 her expected utility must be at least as great. Furthermore, given the model structure, the expected utility gains are strictly positive, as prices with trade will differ from autarkic prices with probability 1.

Combining part (1) with the result above that farmers' gains from trade are zero in the absence of volatility, part (2) follows immediately. Intuitively, volatility amplifies the gains from trade via two mechanisms. First, on the consumption side, farmers are now able to maintain a more balanced consumption basket by trading crops with relatively good yield realizations to purchase crops with relatively bad yield realizations—essentially, volatility creates an option value of trading away good harvests that is not present in the absence of volatility. Second, on the production side, by decoupling production and consumption decisions, trade allows farmers to alter their planting decisions in order to reduce their risk exposure. However, part (3) shows that additional volatility—for example, making "safe" crops more volatile—can attenuate the gains from trade by reducing farmers' ability to use their crop allocation to reduce their risk; Table B.7 in Online Appendix B offers an example.

It is important to emphasize that Proposition 3 hinges on the assumption that farmers can produce all that they wish to consume; if, for example, farmers also consume manufactures they cannot produce, as in Newbery and Stiglitz (1984), gains from trade in the presence of volatility need not be positive—a possibility we introduce in the quantitative version of our model below.[19]

5. QUANTIFYING THE WELFARE EFFECTS OF TRADE AND VOLATILITY

We now bring the framework developed above to the rural Indian data to quantify the welfare effects of trade in the presence of volatility.

5.1. *Extending the Baseline Model*

We first extend the basic framework above to create a "quantitative" model that adds realism by incorporating a number of additional features.

Constant Elasticity of Substitution Preferences. In the baseline model above, we assumed that agents consumed a Cobb–Douglas aggregate of goods; we now generalize to constant elasticity of substitution (CES) preferences with elasticity of substitution σ ($\bar{\sigma}$) for village (market) residents.

A Manufacturing Good. In the baseline model, we assumed that farmers are able to produce all goods in the economy; while convenient, certain goods (such as services or manufacturing) are less commonly produced in rural India. As noted above, the presence of such goods has potentially important implications for the gains from trade. We extend the model to incorporate a numeraire good $g = 0$ that is produced only in markets. This numeraire good is costlessly traded and agents have Cobb–Douglas preferences across the good and the (CES) consumption bundle of agricultural goods (with β_i equal to the agricultural expenditure share).

Finite Number of Villages With Correlated Productivity Shocks. We amend Assumption 1 to allow for arbitrary yield correlations across crops and a finite number N of villages:

ASSUMPTION 2—Log-normal distribution of yields (generalized): *Assume that the joint distributions of yields across all goods and villages are log-normally distributed across states of the world. In particular, define* $\mathbf{A}(s)$ *as the* $(G \times N) \times 1$ *vector of* $\{A_{ig}(s)\}_{g\in\mathcal{G},i\in\mathcal{N}}$. *Then* $\ln \mathbf{A} \sim N(\mu^A, \mathbf{\Sigma}^A)$, *where* $\boldsymbol{\mu}^A \equiv [\mu^A_{ig}]$ *is a* $GN \times 1$ *vector and* $\mathbf{\Sigma}^A \equiv [\Sigma^A_{ig,jh}]$ *is a* $GN \times GN$ *variance-covariance matrix*.

[19] Newbery and Stiglitz (1984) provided an extreme example where farmers only wish to consume non-farm goods whose productivity is not volatile while non-farm producers only wish to consume volatile farm goods.

With a finite number of villages and correlated yield shocks, equilibrium market prices are now state dependent. As a result, the volatility of famers' real income will be affected not only by changes in a village's own trade costs but also changes in trade costs elsewhere in the network. As we will see below, this new second-moment effect will have important quantitative implications.

Multiple Markets. In the baseline model, we assume that all villages trade with the same central market. To better capture India's hierarchical trading network described in Section 2.2, we now incorporate multiple layers of markets. While in principle the model can be extended to include an arbitrary number of layers, given data limitations we consider a three-layer hierarchy where each village $i \in \mathcal{N}$ (an Indian district in our empirics) trades with a regional market $m \in \mathcal{M} \equiv \{1, \dots, M\}$ (the largest city within each state in our empirics), which in turn trades with a central market (Delhi in our empirics). Panel (c) of Figure 1 depicts the resulting trading network.[20]

5.1.1. *The Quantitative Model: A Summary*

We briefly summarize how the results presented in Section 4 change with these model extensions; Online Appendix B.4 provides further details.

Equilibrium Prices. Conditional on the equilibrium regional market prices, the arbitrage process between villages and their regional markets remains unchanged, allowing us to generalize the equilibrium price equation (10) to

$$\ln p_{ig}(s) = -\frac{1}{\sigma + \varepsilon_i} \ln A_{ig}(s) + \frac{\varepsilon_i}{\sigma + \varepsilon_i} \ln \bar{p}_{m(i)g}(s) + \delta_{ig} + \delta_i(s), \tag{19}$$

where δ_{ig} is a location-good term that is constant across all states of the world and $\delta_i(s)$ is a location-state of world term that is the same across all goods.[21] Echoing equation (10), the equilibrium price in a location $\ln p_{ig}(s)$ responds less to local yield shocks and more to prices in its regional market $\ln \bar{p}_{m(i)g}(s)$ as trade costs fall (i.e., ε_i increases).

The fractal nature of the hierarchical trading network means that a very similar expression governs the equilibrium regional market prices $\ln \bar{p}_{mg}(s)$:

$$\ln \bar{p}_{mg}(s) = -\frac{1}{\bar{\sigma} + \varepsilon_m} \ln \bar{Q}_{mg}(s) + \frac{\varepsilon_m}{\bar{\sigma} + \varepsilon_m} \ln p^*_g(s) + \delta_{mg} + \delta_m(s), \tag{20}$$

where $\bar{\sigma}$ is the regional market resident's elasticity of substitution across agricultural goods, ε_m is the Pareto shape parameter governing the distribution of trade costs across traders engaging in arbitrage between regional market m and the central market, $\bar{Q}_{mg}(s)$ is the net quantity of a good that arrives to the market, δ_{mg} is a market-good term that is constant across all states of the world, and $\delta_m(s)$ is a market-state of world term that is the same across all goods.[22] Similarly to village-level prices, regional market prices depend

[20]While there is also a trade across villages within a district (see Figure 1), comprehensive agricultural data at the sub-district level do not exist. We also omit an easy-to-accommodate international trade layer linking the central market with a world market given India's highly restrictive agricultural trade regime during our sample period.

[21]In particular, $\delta_{ig} \equiv \frac{1}{\sigma+\varepsilon_i} \ln(\beta_i \alpha_{ig} / L_i \theta_{ig})$ and $\delta_i(s) \equiv \frac{1}{\sigma+\varepsilon_i} \ln(Y_i(s) / \sum_{h=1}^G \alpha_{ih}(p_{ih}(s))^{1-\sigma})$.

[22]In particular, $\delta_{mg} \equiv \frac{1}{\sigma+\varepsilon_m} \ln \alpha_{mg}$ and $\delta_m(s) \equiv \frac{1}{\sigma+\varepsilon_m} \ln(\beta_m \bar{Y}_m(s) / \sum_{h=1}^G \alpha_{mh}(\bar{p}_{mh}(s))^{1-\sigma})$.

both on the quantity of goods that arrive at the market and on the central market prices $\ln p_g^*(s)$. And, as above, lower trade costs (i.e., higher ε_m) increase the responsiveness to the latter relative to the former.

Equilibrium Crop Choice. As in the baseline model, we apply a second-order approximation to characterize the distribution of farmers' real returns across states of the world; we additionally apply a first-order log-linear approximation of the equilibrium regional market prices around their (log) mean yield to incorporate the fact that market prices are state dependent. These approximations imply farmer real income is approximately log-normally distributed with mean μ_i^Z and variance $\sigma_i^{2,Z}$ defined by equations (76) and (78) in Online Appendix B. The first-order conditions from the farmer's crop choice then again follow equation (17), where the marginal effect on the log of mean real income and variance of log real income, μ_{ig}^Z and σ_{ig}^Z, are defined in equations (79) and (80) in Online Appendix B. The intuition remains as before: farmers equate the marginal increases in risk adjusted real returns across all crops, where the risk-return trade-off is determined by the farmer's effective level of risk aversion. The farmer's first-order conditions imply the following equilibrium crop choice (which generalizes equation (18)):

$$\theta_{ig} = \frac{\alpha_{ig} B_{ig}^{\varepsilon_i + \sigma - 1} \bar{p}_{m(i)g}^{\varepsilon_i}}{\sum_{h=1}^{G} \alpha_h B_{ih}^{\varepsilon_i + \sigma - 1} \bar{p}_{m(i)h}^{\varepsilon_i}}, \tag{21}$$

where B_{ig} is again the risk adjusted productivity (defined in equation (82) in Online Appendix B).

To summarize, the quantitative model remains tractable while being a more realistic description of India. And as in the baseline model, two sets of structural parameters play key roles in determining the strength of the central economic forces. First, the distribution of trade costs ($\{\varepsilon_i\}$ and $\{\varepsilon_m\}$) determines the relative responsiveness of local prices to local shocks and to prices elsewhere—and hence how trade affects volatility. Second, the effective risk aversion parameters ($\{\rho_i\}$) determine how farmers trade off risk versus return—and hence how they respond to changes in volatility. We turn now to the estimation of these key parameters.

5.2. *Estimation of Structural Parameters*

We now summarize the estimation of the structural parameters—with particular attention paid to the key trade cost distributions and effective risk aversion parameters highlighted above; Online Appendix B.6 provides further details.

Observed Parameters: Budget Shares, Market Sizes, and the Distribution of Yields

We choose district-specific agricultural expenditure shares β_i and district-crop-specific CES demand shifters α_{ig} to match observed district-average expenditure shares from the 1987–1988 NSS described in Section 2.3; see Table B.8 in Online Appendix B for summary statistics. Regional and central market preferences are set equal to the average preferences of their constituent districts.

We set the size of each district to its average total cropped area. We set the size of each regional market—which determines the quantity of the numeraire good it produces—so that its size (relative the total size of all its constituent districts) matches the observed urban-rural population ratio in the state, thereby ensuring that each person in India either grows crops on one unit of land or produces one unit of the numeraire good. We set the size of the central market to match the relative size of Delhi compared to the total urban population of India.

We draw the distribution of (log) yields in each decade from the data by treating each year within the decade as an independent draw from a common underlying distribution.[23] Figures B.2 and B.3 in Online Appendix B depict the distribution of mean (log) yields as well as the full variance-covariance matrix across crops and districts for the 1970s, with both displaying substantial heterogeneity.

Estimating the Trade Openness and Elasticities of Substitution

Treating each year as a different realized state of the world, the empirical analog of equation (19) provides a simple and intuitive equation for estimating district i trade openness each decade d, ε_{id}:

$$\ln p_{igtd} = -\frac{1}{\sigma + \varepsilon_{id}} \ln A_{igtd} + \frac{\varepsilon_{id}}{\sigma + \varepsilon_{id}} \ln \bar{p}_{m(i)gtd} + \delta_{igd} + \delta_{itd} + \nu_{igtd}, \tag{22}$$

where δ_{igd} and δ_{itd} are district-crop-decade and district-year-decade fixed effects, respectively, and the residual ν_{igtd} captures measurement error in district prices p_{igtd}, district yields A_{igtd}, and regional market prices $\bar{p}_{m(i)gtd}$. Consistent with the empirical context described in Section 2.2, we treat each Indian state as its own regional market. Because we do not directly observe regional market prices, we set $\bar{p}_{m(i)gtd}$ equal to quantity-weighted average state prices. Similarly to Section 3, we instrument with the rainfall-predicted yields and state-level average prices leaving out own-district prices to: (a) correct for potential endogeneity in yields (e.g., farmers putting more care into high price crops); (b) avoid the mechanical reflection problem in the market-level price; and (c) correct for classical measurement error in yields and market prices.

As a first pass, we recover a common trade openness parameter, that is, $\varepsilon_{id} = \varepsilon$, along with the elasticity of substitution σ, directly from the estimated regression coefficients. The IV specification is reported in column 2 of panel (a) of Table IV and implies $\varepsilon = 2.1$ and $\sigma = 6.2$. However, these averages belie substantial variation across space and time. Echoing Stylized Fact 1, columns 3 and 4 interact yields and prices with within-state market access $\text{MA}_{id}^{\text{instate}}$ and find that prices are both less responsive to local yield shocks and more responsive to state-market prices when the highway system expands. Thus, to estimate district-decade openness ε_{id}, we impose the parameterization $\varepsilon_{id} = \beta_0 + \beta_1 \text{MA}_{id}^{\text{instate}}$ and estimate β_0 and β_1 using GMM and the same moment conditions as our IV specification. Column 6 of panel (a) of Table IV presents these results. Consistent with districts becoming more open with highway improvements, we find average values of ε_{id} growing from 1.9 in the 1970s to 2.2 in the 2000s. We estimate an elasticity of substitution of $\sigma = 6.0$ across crops.

As discussed above, equilibrium market-level prices are characterized much like district-level prices given the fractal nature of the hierarchical trading structure. Accordingly, our estimation of market-level trade openness $\bar{\varepsilon}_{md}$ and the elasticity of substitution $\bar{\sigma}$ proceeds similarly to their district-level analogs (except we allow them to vary with

[23] Consistent with this assumption, we find no serial correlation in (log) yields within crop-district-decade.

TABLE IV

ESTIMATED OPENNESS TO TRADE.

Panel (a): District-Level Openness (ϵ_i)

Dependent Variable:	District Price ($\ln p_{igt}$) (1) OLS	(2) IV	(3) OLS	(4) IV	(5) GMM	(6) GMM
Log yield	−0.034	−0.120	−0.040	−0.151		
	(0.002)	(0.006)	(0.004)	(0.010)		
$MA^{instate}$ × Log yield			0.322	1.576		
			(0.178)	(0.420)		
Log state price	0.385	0.256	0.382	0.227		
	(0.009)	(0.014)	(0.013)	(0.021)		
$MA^{instate}$ × Log state price			0.142	1.375		
			(0.438)	(0.616)		
District trade openness (ϵ_i)	11.315	2.134			2.134	1.705
	(0.913)	(0.190)			(0.190)	(0.240)
District trade openness (ϵ_i) × $MA^{instate}$						16.860
						(7.215)
District elasticity of substitution (σ)	18.084	6.196			6.196	5.969
	(1.309)	(0.307)			(0.307)	(0.284)
Observations	85,918	85,918	85,918	85,918	85,918	85,918
First Stage F-statistic		7293.04		3095.02	291.99	150.50
Crop-District-Decade FE	Yes	Yes	Yes	Yes	Yes	Yes
District-Year-Decade FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel (b): State Market Access (ϵ_m)

Dependent Variable:	State Price ($\ln \bar{p}_{mgt}$) (1) OLS	(2) IV	(3) OLS	(4) IV	(5) GMM	(6) GMM
Log state quantity	−0.097	−0.146	0.020	0.075		
	(0.021)	(0.048)	(0.049)	(0.141)		
Travel time to Delhi × Log state quantity			0.122	0.229		
			(0.054)	(0.150)		
Log India price	0.549	0.287	0.296	0.172		
	(0.064)	(0.058)	(0.115)	(0.104)		
Travel time to Delhi × Log India price			−0.261	−0.118		
			(0.133)	(0.120)		
State trade openness (ϵ_m)	5.643	1.967			1.967	1.126
	(1.445)	(0.818)			(0.546)	(0.694)
State trade openness (ϵ_m) × Travel time to Delhi						−0.725
						(0.850)
State elasticity of substitution (σ)	4.645	4.881			4.881	4.531
	(1.147)	(1.602)			(1.181)	(1.448)
Observations	6870	6870	6870	6870	6870	6870
First Stage F-statistic		651.22		192.18	8.49	4.64
Crop-State-Decade FE	Yes	Yes	Yes	Yes	Yes	Yes
State-Year-Decade FE	Yes	Yes	Yes	Yes	Yes	Yes

(*Continues*)

TABLE IV

Continued.

Note: Each observation is a crop-district-year triplet (panel (a)) or a crop-state-year triplet (panel (b)). The dependent variable in columns (1)–(4) is the (log) price in the district (panel (b)) or state (panel (b)), where the state price is the total value produced in the state (at district-level prices) divided by the total quantity produced in the state. In columns (2) and (4), yields/quantities are instrumented with rainfall predicted yields/quantities, respectively, and prices are instrumented with prices in the rest of the state (panel (a)) or the rest of the country (panel (b)). Columns (5) and (6) use a GMM specification, where column (5) replicates the results of column (2) and column (6) allows for the implied openness measures to vary with within-state market access (panel (a)) or distance to Delhi (panel (b)). Each observation is weighted by the total area in the district (panel (a)) or state (panel (b)) within a decade. Robust standard errors are reported in parentheses.

travel time to Delhi rather than MA_{id}^{instate}) and is summarized in Table IV panel (b) with further details relegated to Online Appendix B.6.[24]

Estimating the Effective Risk Aversion and Costs of Cultivation

Recall that farmers choose a land allocation along their mean-variance frontier, with the gradient at the chosen allocation equal to their effective risk aversion parameter ρ_{id}. This relationship is summarized by the farmer's first-order conditions (equation (17)), which we rewrite as

$$\mu_{igd}^{Z} = \rho_{id}\sigma_{ig}^{Z} + \delta_{id} + \delta_{ig} + \delta_{gd} + \zeta_{igd}, \tag{23}$$

where the marginal contribution to the mean and variance of real returns, μ_{ig}^{Z} and σ_{ig}^{Z}, are calculated from the mean and variance-covariance of the (observed) nominal gross yields $\boldsymbol{\mu}^{A}$ and $\boldsymbol{\Sigma}^{A}$ (see equations (79) and (80) in Online Appendix B). The δ_{id} fixed effect is the district-decade level Lagrange multiplier λ_{id}, while a district-good fixed effect δ_{ig}, a crop-decade fixed effect δ_{gd}, and an idiosyncratic district-good-decade error term ζ_{igd} together capture any unobserved differences in the cost of cultivation across crops (i.e., we calibrate the unobserved crop costs so that farmers in all districts and all decades are producing at the optimal point along their mean-variance frontier). Given that our variance-covariance matrix is an estimate, to correct for (classical) measurement error, we instrument for the marginal contribution to the variance term σ_{ig}^{Z} with an instrument constructed using the rainfall predicted variance-covariance matrix of log yields.

Table V first presents results assuming a common effective risk aversion parameter $\rho_{id} = \rho$. Mean real returns are increasing in the variance of real returns with the IV estimates implying a ρ slightly greater than 1 ($\rho = 1.3$), consistent with previous estimates of risk aversion of Indian farmers (e.g., Rosenzweig and Wolpin (1993)). Consistent with Stylized Fact 2, we allow ρ_{id} to be a function of rural bank access, with a parameterization $\rho_{id} = \rho^{A}\text{bank}_{id} + \rho^{B}$. Column 4 of Table V presents our preferred estimate and shows that farmers choose less conservative crop allocations when they have greater bank access, with an average effective risk aversion of 2.2 (with an interquartile range of 0.8) in the 1970s, which falls to 1.2 in the 2000s (interquartile range of 0.9). Reassuringly, the combination of the fixed effects and residuals from regression (23)—which we interpret as the unobserved crop costs that ensure the crop choices we observe are optimal from the farmer's perspective—positively correlate with the actual crop costs we observe at the state level for a subset of our sample period; see Table B.9 in Online Appendix B.

[24]We find that the average values of $\bar{\varepsilon}_{im}$ increase only slightly from 1.91 to 1.94 as a result of Indian highway expansion. We estimate an elasticity of substitution of $\bar{\sigma} = 4.8$ across crops.

TABLE V

ESTIMATED EFFECTIVE RISK AVERSION.

	Mean Real Returns (μ_{ig}^{Z})			
Dependent Variable:	(1) OLS	(2) IV	(3) OLS	(4) IV
Variance of real returns (σ_{ig}^{Z})	0.554	1.325	1.710	3.265
	(0.224)	(0.429)	(0.443)	(1.111)
Variance of real returns (σ_{ig}^{Z}) $\times$ Banks			−0.310	−0.454
			(0.098)	(0.217)
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		421.468		76.953
R-squared	0.969	−0.004	0.969	−0.005
Observations	14,916	14,916	14,916	14,916

Note: Each observation is a crop-district-decade triplet. The dependent variable is the marginal contribution of a crop to (log) mean real returns (μ_{ig}^{Z}). The independent variable is the marginal contribution of a crop to the variance of (log) real returns (σ_{ig}^{Z}) and, in columns (3) and (4), its interaction with rural banks per capita. In IV columns, the variance of real returns is instrumented using the variance-covariance matrix of rainfall predicted yields instead of the actual variance-covariance matrix. Both the dependent and independent variables are winsorized at the 1%/99% level. Each observation is weighted by the total area allocated to the crop within a district-decade. Robust standard errors are reported in parentheses.

5.3. *The Welfare Impacts of the Expansion of India's Highway Network*

We now use our structural estimates to quantify the welfare effects of the expansion of the Indian highway network. We first consider the impact of highway expansion in isolation, holding all structural parameters, including the access to banks, constant at their 1970s levels except for the district- and state-level trade costs ε_{id} and $\bar{\varepsilon}_{md}$. We allow these trade costs to evolve to match observed changes in within-state market access and travel time to Delhi as described in Section 5.2. We then calculate the equilibrium distributions of real incomes and crop choices in all districts; see Online Appendix B.5 for details. Finally, we calculate the equilibrium realized real income in all locations using the realized yields in each year in the 1970s. This procedure ensures that effects depend on the log-normal approximation above only through farmers' optimal crop choice.

Panel (a) of Table VI presents the results, reported as the percentage change relative to the 1970s averaged across districts.[25] On its own, the expansion of the Indian highway network between the 1970s and 2000s increased mean real incomes for farmers by 2.2%. This rise was accompanied by a small decrease in the variance of real income, leading to an increase in expected welfare of 2.3%. Lower trade costs, and the associated decline in arbitrage revenue going to traders, resulted in declines in the average mean real income of market residents—including traders, drivers, and producers of the homogeneous good—of 0.9% and small declines in the variability of their real income.

These average effects belie substantial spatial heterogeneity. Panel (a) of Figure 4 plots changes in within-state market access between the 1970s and 2000s. Panel (b) shows that

[25]We report welfare as the percentage increase in nominal income that an agent receives with certainty, holding all parameters at their 1970s values, that would yield the equivalent change in expected utility as from the counterfactual, that is, the certainty equivalent variation (CEV). See equation (48) and the surrounding discussion in Appendix A.3.3.

TABLE VI

WELFARE IMPACT OF THE EXPANSION OF THE INDIAN HIGHWAY NETWORK.

Panel (a): Highway Expansion Only

	Districts						Markets	
			Welfare					
	(1) Mean	(2) Variance	(3) $\theta_{R,B}, \rho_B$	(4) $\theta_{\not{R},\not{B}}, \rho_B$	(5) $\theta_{\not{R},B}, \rho_B$	(6) $\theta_{R,B}, \rho_{\not{B}}$	(7) Mean	(8) Variance
	2.237	−0.048	2.297	0.000	0.000	2.297	−0.926	−0.008
	(0.178)	(0.008)	(0.177)	(.)	(.)	(0.177)	(0.702)	(0.003)
N	311	311	311	311	311	311	17	17

Panel (b): Highway and Bank Expansion

	Districts						Markets	
			Welfare					
	(1) Mean	(2) Variance	(3) $\theta_{R,B}, \rho_B$	(4) $\theta_{\not{R},\not{B}}, \rho_B$	(5) $\theta_{\not{R},B}, \rho_B$	(6) $\theta_{R,B}, \rho_{\not{B}}$	(7) Mean	(8) Variance
	2.843	0.692	4.388	1.874	2.160	2.082	−0.906	0.004
	(0.201)	(0.123)	(0.242)	(0.176)	(0.192)	(0.204)	(0.725)	(0.002)
N	311	311	311	311	311	311	17	17

Panel (c): Highway and (Counterfactual) Improved Bank Expansion

	Districts						Markets	
			Welfare					
	(1) Mean	(2) Variance	(3) $\theta_{R,B}, \rho_B$	(4) $\theta_{\not{R},\not{B}}, \rho_B$	(5) $\theta_{\not{R},B}, \rho_B$	(6) $\theta_{R,B}, \rho_{\not{B}}$	(7) Mean	(8) Variance
	3.130	1.311	5.926	3.041	3.704	1.633	−0.956	0.018
	(0.217)	(0.238)	(0.326)	(0.258)	(0.303)	(0.281)	(0.775)	(0.008)
N	311	311	311	311	311	311	17	17

Note: This table reports the estimated effects of the Indian highway expansion. In panel (a), we hold the effective risk aversion parameter in each district at its 1970s value. In panel (b), we allow each district's effective risk aversion parameter to change based on its observed change in bank access. In panel (c), we consider a counterfactual where all districts are given effective risk aversion parameters consistent with being in the upper quartile of rural bank access from the 1980s onward. In columns 1 and 2, we report the average change across districts in the (log of the) mean real returns and the variance of (the log of) real returns, respectively. Columns 3–6 report the change in welfare measured as the certainty equivalent variation (CEV), that is, the percentage increase in income that an agent receives with certainty that would generate the equivalent change in expected utility as the counterfactual in question, with the θ and ρ denoting crop choice and effective risk aversion, respectively, the subscript R ($\not{R}$) indicating that the road expansion did (did not) occur, and B ($\not{B}$) indicating that the bank expansion considered in the panel did (did not) occur. That is, column 3 reports the actual CEV from both the road and bank expansion; column 4 reports the CEV using the 1970s crop allocation but allowing the bank expansion to occur; column 5 reports the CEV calculating the optimal crop re-allocation from only the bank expansion; and column 6 reports the CEV using the same crop allocation as in column 3 but evaluating the welfare using the 1970s effective risk aversion parameters. All values are log differences multiplied by 100. Standard errors are reported in parentheses.

districts whose within-state market access grew the most experienced greater increases in the mean of their real income. Column 1 of Table VII projects the district-level gains for each decade on within-state market access and the crop-area weighted average of within-state market access for all other districts in the same state; consistent with gains coming

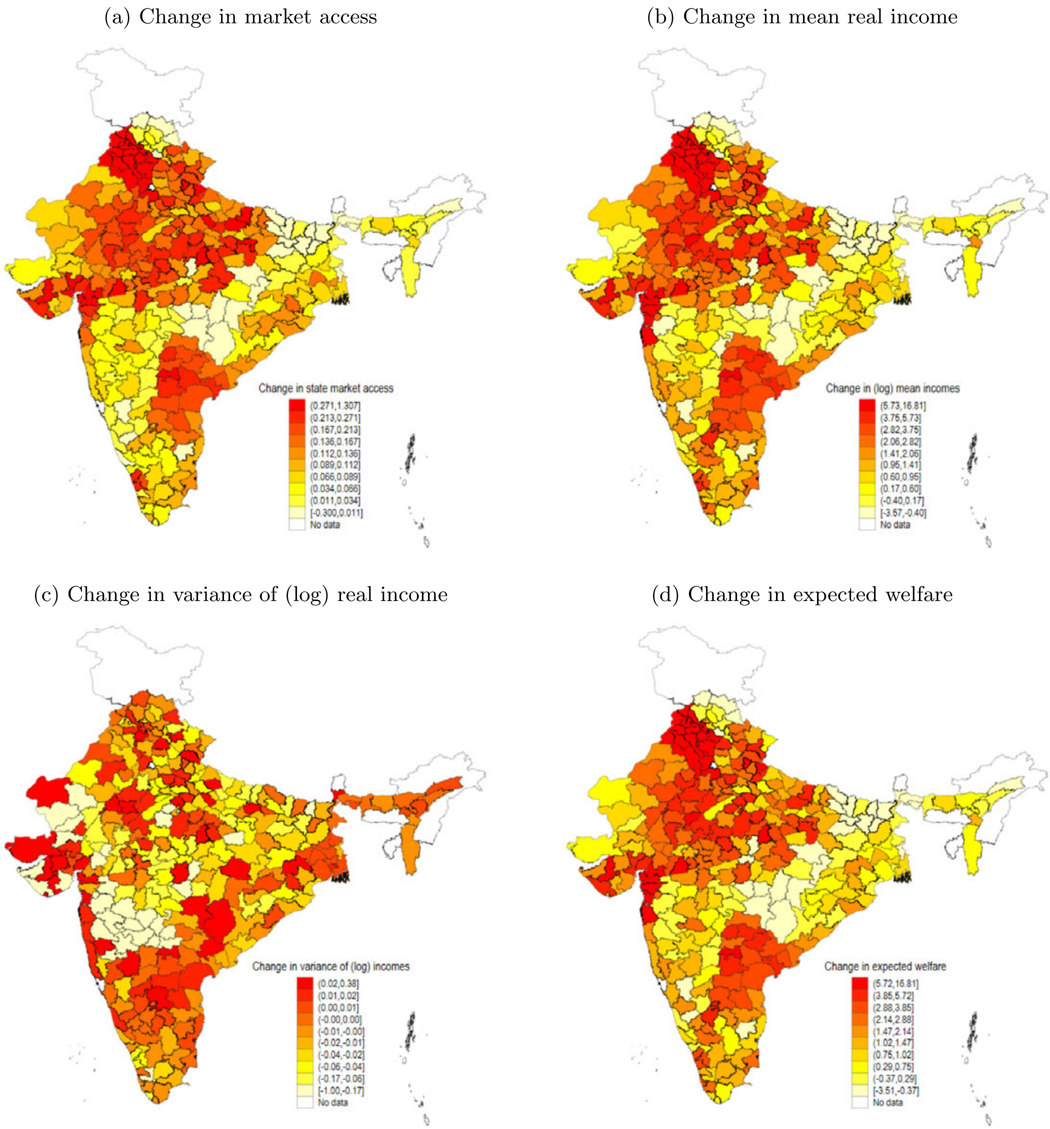


FIGURE 4.—The spatial distribution of the gains from trade. *Note*: This figure presents the spatial distribution of the gains from trade resulting from the expansion of the Indian highway network from the 1970s to the 2000s. Panel (a) depicts the change in the observed (within-state) market access; panel (b) depicts the change in the (log of) mean real income; panel (c) depicts the change in the variance (of the log) of real income; and panel (c) depicts the change in expected welfare. The units of panels (b), (c), and (d) are log basis points (i.e., approximately percentage points). In all panels, reds (yellow) indicate higher (lower) deciles of changes.

primarily through improvements in a district's own market access, the coefficient on own market access is more than five times larger than that on market access improvements elsewhere in the state.

A different pattern emerges for the impact of the highway expansion on volatility. Even though real income volatility declines by a small amount on average, an analogous analysis—see panel (c) of Figure 4 and column 2 of Table VII—shows that districts with

TABLE VII

EXPLAINING THE HETEROGENEITY ACROSS DISTRICTS IN THE GAINS FROM THE EXPANSION OF THE INDIAN HIGHWAY NETWORK.

Dependent Variable:	Mean (1)	Variance (2)	Welfare (3)
$MA^{instate}$	138.211	0.901	137.032
	(19.459)	(0.450)	(19.526)
$MA^{instate}$ elsewhere in state	25.838	−1.998	28.533
	(15.382)	(0.676)	(15.320)
District FE	Yes	Yes	Yes
R-squared (within)	0.853	0.016	0.858
Observations	1244	1244	1244

Note: Each observation is a district-decade pair; there are 4 decades and 311 districts. The dependent variables are the effect of the Indian highway expansion on the (log of the) mean real returns (column 1), variance of (the log of) real returns (column 2), and the expected welfare (column 3), respectively, holding all other parameters constant at 1970s levels. State market access elsewhere in the state is the crop-area weighted average state market access in that decade for all other districts within the state. Units are in log basis points (i.e., approximately percentage points). Standard errors clustered at the district level are reported in parentheses.

the greatest improvements in their own within-state market access actually saw their real incomes become *more* volatile. As Sections 3 and 4 highlight, declines in one's own trade costs reduce the insurance that the response of local prices to local yield shocks naturally provides. But greater integration elsewhere has an opposite effect, reducing volatility by making market prices less susceptible to idiosyncratic shocks. As a result of these opposing forces, real income volatility only increased in 111 of 311 districts. Finally, as panel (d) of Figure 4 and column 3 of Table VII illustrate, the welfare gains that combine both these first- and second-moment effects come from improvements in own and others' market access.

5.4. *Improvements in Risk Mitigating Technologies and the Gains From Trade*

We now turn to examining how the growth in rural bank access—a risk mitigation technology—altered the impacts of the highway expansion. As we saw in Stylized Fact 2 and Section 5.2, farmers were willing to incur greater risk in their crop allocations as bank access improved. How did this fall in farmers' effective risk aversion affect the gains from trade? To answer this question, Table VI panel (b) examines the combined impact of highways and banks by allowing both trade costs, ε_{id} and $\bar{\varepsilon}_{md}$, and effective risk aversion, ρ_{id}, to evolve together based on the observed expansions of highways and banks. Increases in the number of rural banks per capita encouraged farmers to pursue more risky crop allocations than they would have with the highway expansion alone. Relative to our previous counterfactual that held banks at their 1970s levels, mean real incomes rise by an additional 0.6 percentage points—a 27% increase. To achieve these greater mean incomes, farmers incurred greater risk, substantially increasing the volatility of real income, with the variance of log real income now rising by 0.7. The welfare gains nearly double from 2.3% to 4.4%.

Panel (c) of Table VI further asks how much greater would the gains from highway expansion have been if rural India had uniformly-good bank access. To do so, we bring any district below the 75th percentile of bank access in a particular decade up to the 75th percentile. Both the mean and variance of incomes rise further as farmers pursue even higher-risk higher-return cropping strategies, with welfare gains climbing to 5.9%.

From where did the additional welfare gains in panels (b) and (c) arise? Improved bank access makes volatility less costly and allows farmers to pursue riskier crop allocations. But improvements in bank access and infrastructure may also be substitutes, encouraging farmers to reallocate crops in incompatible ways. To explore these effects, we first calculate the direct impact of bank access by changing effective risk aversion to account for improved bank access (denoted by $\rho = \rho_B$), but holding crop allocations (denoted by $\theta = \theta_{\not{R},\not{B}}$) and trade costs at their 1970s levels; column 4 presents these results.[26] We then assess the total impact of bank access on welfare by also allowing crop allocations to respond to the change in ρ still holding trade costs at 1970s levels (i.e., $\theta = \theta_{\not{R},B}$, $\rho = \rho_B$); column 5 presents these results. Focusing on panel (b) and comparing these numbers to the 2.1 percentage point (4.4%–2.3%) increase in welfare relative to panel (a), we find that most of the additional welfare gains arise from the direct impact of banks on the welfare cost of volatility. And, if anything, there is a small amount of substitution between improvements in bank access and infrastructure, as the welfare gains from panel (b) column 5 are slightly greater than the difference in welfare between panel (b) column 3 and panel (a) column 3.

These mean effects again mask substantial heterogeneity across districts. Column 1 of Table VIII projects the additional welfare gain from the combination of banks and highways relative to highways alone on within-state market access, the change in effective risk aversion from improved bank access (i.e., $\rho_{i,d} - \rho_{i,70s}$), and the interaction of the two. Both highways and banks increase welfare, but act as substitutes on average. Column 2 shows that whether the two are substitutes or complements hinges on whether the riskiest crops are also the comparative advantage ones. In districts where riskier crops have higher yields (i.e., the mean and variance of log yields correlate positively), banks and highways are complements; in these locations, farmers need to act more risk loving to take full advantage of first-moment gains from trade. Conversely, column 3 finds that highways and banks are substitutes when riskier crops have lower yields, as here reallocating toward comparative advantage crops also reduces volatility. Column 4 confirms this heterogeneity via a triple interaction between market access, changes in risk aversion, and mean-variance correlations.

If allocations with higher mean real incomes were available, why did farmers not pursue them without the bank expansion? Column 6 of Table VI answers this question by evaluating the change in welfare from each panel's chosen crop reallocations had effective risk aversion been fixed at the level consistent with 1970s bank access (i.e., $\theta = \theta_{R,B}$, $\rho = \rho_{\not{B}}$). In both panels (b) and (c), the welfare gains from the more aggressive crop allocations would have been smaller than for the crop choices in panel (a). That is, farmers were only willing to pursue the riskier crop allocations necessary to achieve greater first-moment returns if they also had better risk mitigation technologies.

Taken together, our structural results imply that while first-moment gains from specialization outweigh any second-moment losses, better access to risk mitigating technologies amplifies the gains by encouraging farmers to take advantage of higher-return higher-risk crop allocations—with the degree of amplification determined by whether riskier crops are also comparative advantage crops.

[26]As above, we report the CEV. In these counterfactuals, we hold fixed farmers' innate risk aversion but allow their effective risk aversion to change with technological improvements (i.e., bank access). Appendix A.3.3 microfounds this approach including the expression for the CEV.

TABLE VIII

THE ADDITIONAL GAINS FROM THE INDIAN HIGHWAY NETWORK EXPANSION WITH IMPROVED BANK ACCESS.

	Additional Welfare			
Dependent Variable:	(1)	(2)	(3)	(4)
$\text{MA}^{\text{instate}}$	10.023	−41.251	14.164	−23.866
	(5.574)	(22.596)	(6.931)	(11.113)
Δ Effective risk aversion $(\rho_{i,d} - \rho_{i,70s})$	−2.548	−0.858	−3.048	−1.847
	(0.310)	(0.217)	(0.392)	(0.231)
$\text{MA}^{\text{instate}} \times (\rho_{i,d} - \rho_{i,70s})$	27.003	−32.058	37.992	−3.695
	(8.385)	(16.580)	(10.090)	(9.512)
$\text{MA}^{\text{instate}} \times \text{Corr}(\mu^A_{i,g}, \sigma^A_{i,g})$				−129.013
				(43.171)
$(\rho_{i,d} - \rho_{i,70s}) \times \text{Corr}(\mu^A_{i,g}, \sigma^A_{i,g})$				3.155
				(1.162)
$\text{MA}^{\text{instate}} \times (\rho_{i,d} - \rho_{i,70s}) \times \text{Corr}(\mu^A_{i,g}, \sigma^A_{i,g})$				−122.454
				(45.026)
District FE	Yes	Yes	Yes	Yes
R-squared (within)	0.354	0.518	0.374	0.387
Observations	1244	244	1000	1244
Sample	Full	$\text{Corr}(\mu^A_{i,g}, \sigma^A_{i,g}) > 0$	$\text{Corr}(\mu^A_{i,g}, \sigma^A_{i,g}) < 0$	Full

Note: Each observation is a district-decade pair; there are 4 decades and 311 districts. The dependent variable is the additional impact of the Indian highway expansion and rural bank expansion on welfare relative to the Indian highway expansion alone holding all other parameters constant at 1970s levels. Column 2 (3) only includes districts where the correlation across crops within district of the log mean yield and the variance of log yields is positive (negative) in the 1970s, that is, districts where the high (low) return crops are more riskier. Welfare is measured as the percentage increase in nominal income that an agent receives with certainty that would yield the equivalent change in expected utility as from the counterfactual, that is, the certainty equivalent variation (CEV). Standard errors clustered at the district level are reported in parentheses.

6. CONCLUSION

This paper examines the relationship between trade and volatility in the context of Indian agriculture. We first document that reductions in trade costs due to the expansion of the Indian highway network reduced the elasticity of local prices to local yields, leading farmers to reallocate their land toward crops with lower yield volatility, especially those farmers with worse access to banks. We then embed a portfolio allocation decision into a novel many-location Ricardian trade model. Risk averse producers choose their optimal allocation of resources across goods. This allocation, along with the distributions of trade costs and yields, determines the general equilibrium distribution of real incomes. The model yields tractable equations governing prices and farmers' resource allocations and matches well 40 years of district-level data on yields, prices, and cropping patterns.

The model provides intuitive and transparent estimating equations that identify both trade costs—using the relationship between local prices, yield shocks, and prices elsewhere—and farmers' risk preferences—using the slope of the mean-variance frontier at the observed crop choices. Using these estimates, we show that first-moment gains from specialization dominate second-moment effects and that improvements in risk mitigating technologies allow farmers to achieve greater first-moment gains by pursuing riskier crop reallocations.

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