MARKET POWER AND SPATIAL COMPETITION IN RURAL INDIA*

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Market power of intermediaries contributes to the low incomes of farmers in India. I study the role of spatial competition between intermediaries in determining the prices that farmers receive in India by focusing on a law that restricts farmers to selling their goods to intermediaries in their own state. I show that the discontinuities in market power generated by the law translate into discontinuities in prices. Increasing spatial competition by one standard deviation causes prices received by farmers to increase by 6.4%. I propose and estimate a quantitative spatial model of bargaining and trade to shed light on spatial and aggregate implications. Estimates from the structural model suggest that removing the interstate trade restriction in India would increase competition between intermediaries. Thereby average farmer prices and their output would increase by at least 11% and 7%, respectively. The value of the national crop output would increase by at least 18%. However, there are distributional consequences as well, as some farmers stand to lose due to increased local production. *JEL Codes:* D43, F12, L13, L81, O13, Q13, R12.

I. INTRODUCTION

Small farmers in low-income countries are among the poorest people in the world. Their revenues may be low partly because they are unproductive but also because they may receive low prices for what they produce. One reason farmers receive low

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prices could be the monopsony power of intermediaries or "middlemen," who are the main buyers of farmers' output in developing economies. A source of their market power is the limited ability of farmers to arbitrage between different intermediaries due to high costs of transportation or policy regulations. This channel of spatial competition between intermediaries, that is, the ability of farmers to conduct spatial arbitrage, may be an important determinant of the income and welfare of farmers. In this article, I use microdata from India on locations of intermediary markets, prices, and data on agriculture production to study the importance of spatial competition between intermediary markets for farmers' incomes and production.

Key to my approach are the Agriculture Produce and Marketing Committee (APMC) Acts of Indian states that restrict farmers to selling their output to government-licensed intermediaries in government-regulated markets of their state. The analysis has two parts. In the first part, I establish that spatial competition between intermediaries is an important determinant of the prices that farmers receive. There are two challenges in analyzing the relationship between spatial competition and prices: first, credibly measuring spatial competition and second, the endogeneity in the location of intermediaries. Besides its intrinsic interest, the Indian context helps me address both challenges. Monopsony rights of the APMC markets and their fixed spatial location allow me to measure competition between markets and relate it to price realizations. More important, the APMC Acts ensure a discontinuity at the border in the competition faced by markets. This allows me to establish a causal relationship between competition and prices. My estimates suggest an average increase of 6.4% in farmer prices due to a one standard deviation increase in spatial competition.

In this context, a policy that would increase spatial competition is the removal of interstate trade restriction. The effects of such a policy change cannot be directly inferred from the data, and evaluating them requires a structural model. Specifically, a reduced-form exercise will fail to capture at least three crucial elements of the change. First, removal of trade restrictions will not only affect the markets on the border but will also cause ripple effects in the markets in the interior of states as farmers eliminate arbitrage between markets. The magnitude of these effects will depend on transportation costs, the actual location of markets, local demand conditions, and cropping patterns. Second, a

change in the prices received by farmers reflects only a part of the benefit. Higher prices then incentivize farmers to reoptimize the use of intermediate inputs and alter production. Third, changes in supply can lead to changes in retail prices of crops, which would feed back into the prices received by farmers.

In the second part of the article, I develop a spatial model of trade in agricultural markets in India to estimate gains from removing interstate trade restrictions. The model uses the economic geography and flexibly captures the determinants of spatial competition. In the framework, postharvest, farmers optimally choose a market to sell their output. At the market, they Nash bargain with the associated intermediary,[1] who in turn sells the purchased goods in the local retail market. When farmers bargain with an intermediary at a market, they alternatively consider transporting their goods to another market nearby and selling at a higher price. Geography and policy create spatial variation in the farmers' outside options and therefore spatial variation in the degree of market power that intermediaries can exert.

I recover a structural relationship between the prices that the farmer receives at a particular market site, the prices in the neighboring markets, and the local retail price. This relationship depends on the Nash-bargaining parameter, geographic location of the markets, and the transport costs. To deal with issues stemming from the simultaneity in the determination of prices at each location, the model parameters are estimated using a method of simulated moments procedure.

Next I use the estimated model to conduct policy counterfactuals in which I remove interstate trade restrictions. This change increases spatial competition between markets. As a result, overall, farmer prices increase by about 9% on average and by 19% for the farmers with above-median gains. Several reasons drive these effects. First, prices increase by 1% on average (and about 2% for the farmers with above-median gains) purely because farmers are in a better negotiating position. In particular, even if farmers' market choice is kept fixed, they can now "threaten" intermediaries by

1. In practice, there may be 15–20 intermediaries in a market, but empirical (Banerji and Meenakshi 2004; Meenakshi and Banerji 2005) and ethnographic (Krishnamurthy 2011) works suggest collusion among intermediaries in these markets. Therefore, in the absence of data on the number of intermediaries in a market, I assume that each market is associated with a representative intermediary.

saying they could access out-of-state markets. Some farmers gain as much as 7% because they are in a better negotiating position.

Farmer prices increase on average by about 11% (and by about 21% for the farmers with above-median gains) when they can also choose to switch their market choices optimally. Farmers close to borders gain much more because, in addition to benefiting from increased competition, they also get access to closer markets, which reduces their transportation costs. These price increases allow farmers to adjust the use of intermediate inputs and expand production by about 9% on average. Because farmers are small and take retail market prices as given, they do not consider the fact that the aggregate demand curve is downward sloping. As a result, this increased supply puts downward pressure on retail and farmer prices. While on net, the average farmer price increases by 9%, some farmers lose out. Among the farmers who lose, the average decline in prices is about 10%.

The quantitative spatial model also allows me to show that spatial competition interacts in important ways with other development policies. The market access of farmers can be increased either by lowering transport costs or by letting them sell in markets in other states. Using the model, I show that there is a large interaction effect of the two policies. Farmers gain substantially more from the simultaneous reduction of transport costs and the elimination of border restrictions to trade than the sum of the gains from enacting each of the two policy changes alone. Moreover, the additional gains occur in locations with greater market power of intermediaries, where reductions in transport costs on their own would not have a large effect.

The quantitative magnitudes from the counterfactual exercises should matter to policy makers. First, they provide an estimate of the gains of a potential reform in India that the central government had been pushing the states toward for over a decade—creating a National Agriculture Market (NAM). Second, the estimates also offer caution. In general equilibrium, there will be distributional consequences as some farmers stand to lose from increased competition. Third, an understanding of the spatial distribution of market power provides insight on policy design that is likely to yield better results for raising farmer incomes (and concomitant poverty alleviation) in specific regions. For example, farmers in more competitive regions are likely to gain more from investments such as road construction. On the other hand, policy makers need to explicitly target competition between

intermediaries in regions where they exert considerable market power. Fourth, while subsidies in the input and output markets have conventionally been the focus of policies meant to improve farmer incomes in developing countries, this article highlights the importance of physical output market sites and policies that restrict market access for farmer incomes. Subsidies not only place a fiscal burden on the exchequer but also distort market prices, whereas gains from implementing policies that increase competition can essentially be achieved with little financial cost.[2]

The work in this article relates to a number of different strands of literature. Most relevant is the work that considers the distribution of gains from trade in the presence of variable markups and intermediation. Although there is recent work that examines gains from trade in the presence of variable markups, the focus has been on producers rather than intermediaries with market power (see Melitz and Ottaviano 2008; Edmond, Midrigan, and Xu 2015; De Loecker et al. 2016). Here I introduce the dimensions of intermediation and spatially varying market power and estimate gains from changes in the market power of intermediaries. In that respect, my work is complementary to Atkin and Donaldson (2015), who show that the market power of intermediaries is an important determinant of actual prices paid by consumers. However, the goal in Atkin and Donaldson (2015) is to separately identify trade costs from market power. I contribute by establishing the microfoundations of a distinctive channel—that of bargaining with spatially varying threat points—through which intermediaries in remote locations may enjoy market power. This is essential to conducting the policy counterfactuals. Grant and Startz (2022) is also closely related, but they seek to understand the structure of supply chains. In particular, their goal is to understand the trade-off between market power and economies of scale that results from increasing the number of intermediaries in a supply chain.

2. Many other policies can increase spatial competition, such as creating new markets or facilitating farmers to directly sell to supermarkets. Quantifying gains from those policy changes will require additional information, such as estimates of the fixed cost of entry of new markets or the location and capacities of existing supermarkets. In the absence of such data, I choose to relax a realistic policy regulation, which allows me to study the same channel without having to worry about other margins.

Although the core mechanism in this study is not surprising and has been conjectured by others (e.g., Dillon and Dambro 2016), the theoretical literature on intermediation and trade (Antràs and Costinot 2011; Bardhan, Mookherjee, and Tsumagari 2013; Krishna and Sheveleva 2017) does not explicitly model it. Estimating spatial competition has been of interest for researchers in the industrial organization literature as well (e.g., Davis 2006; Syverson 2007). I contribute to this literature by building a spatial model of bargaining and trade with intermediation where intermediaries enjoy market power because it is costly for the farmers in remote locations to access alternative buyers.

This article is also related to a growing body of quantitative economic geography literature that estimates welfare gains from integration. For example, Donaldson (2018) and Donaldson and Hornbeck (2016) estimate welfare gains as a result of reductions in transport costs. Allen and Atkin (2022) explore the effect of trade on the link between integration and the volatility of returns for Indian farmers. Although this literature has largely focused on perfectly competitive environments, often building on the seminal work of Eaton and Kortum (2002), I show that gains from integration or reductions in trade costs are heterogeneous in space and the magnitudes relate to the spatial variation in the market power of intermediaries.

The existing empirical literature that measures market power of intermediaries in agricultural markets in low- and middle-income countries (surveyed in Dillon and Dambro 2016) provides mixed evidence, with some papers estimating sizable market power of intermediaries and others finding that it is not so large (e.g., Fafchamps and Gabre-Madhin 2006). Bergquist and Dinerstein (2020), for example, estimate high market power in a setting where most consumers are households, but they do not consider farmer prices. Casaburi and Reed (2022) find that traders are numerous and undifferentiated, indicating little market power at the farm gate. This body of work has focused on testing competitiveness of particular agricultural markets without regard to their spatial locations. Papers either estimate pass-through rates at markets (e.g., Bergquist and Dinerstein 2020), directly measure margins of traders (Fafchamps and Minten 2002), or account for the entry and exit of intermediaries (Fafchamps, Gabre-Madhin, and Minten 2005). This article uses both retail and farm gate prices, and shows that the interaction of economic geography with spatial competition can generate spatially varying market

power for intermediaries. It therefore provides a possible rationale for isolated studies finding different estimates of the market power of intermediaries.

There are three related papers on agricultural markets in India. Banerji and Meenakshi (2004) and Meenakshi and Banerji (2005) analyze transaction-level data from markets in north India to identify collusion among traders. Mitra et al. (2018) estimate high trader margins in the state of West Bengal. They conclude that their results are inconsistent with long-term contracts between farmers and traders but consistent with a model of ex post bargaining. While these papers provide useful insights about the working of these markets, I further contribute to this literature by using microdata to estimate the spatial distribution of the market power of intermediaries in most of India.

Finally, since the seminal work of McCallum (1995), an extensive literature has documented significant costs of crossing national borders (Anderson and van Wincoop 2003; Engel and Rogers 1996). I show that significant border costs exist even within a large developing economy. This article is complementary to Coşar, Grieco, and Tintelnot (2015), which studies spatial competition between wind turbine manufacturers and the effect of the Denmark–Germany border on their production costs.

The rest of the article is organized as follows. In the next section, I provide the institutional background of agricultural trade and production in India. Section III outlines data sources. Section IV presents reduced-form evidence for the main mechanism, that is, spatial competition causing an increase in the prices that farmers get. In Section V, I develop the quantitative framework that I use to conduct policy counterfactuals. Section VI discusses the structural estimation of the model. In Section VII, I study the effect of increased competition from removing interstate trade restrictions on farmer incomes and production. Finally, in Section VIII, I offer concluding remarks.

II. Agricultural Trade in India

I provide a brief description of agricultural trade in India, the current institutional setting, and a brief history of the regulated agricultural markets.

II.A. Empirical Context

Agriculture is an important sector of the Indian economy: in 2011, 54.6% of the total workforce was employed in

agriculture, and the sector generated 18.52% of India's total gross value added.[3] Eight nonperishable crops—rice, wheat, maize, sorghum, barley, finger millet, pearl millet, and soybean—account for 70% of India's gross cropped area. In this article I restrict attention to these crops.

There are two cropping seasons each year: fall or *kharif* (July to November during the southwest monsoon) and spring or *rabi* (November to March). Some regions also have a third summer crop between March and June. Rice, sorghum, maize, millet, and soybean are primarily grown in the *kharif* season, while wheat and barley are grown in the *rabi* season.

The median Indian farming household operates a small farm of 1.5 ha and cultivates it with the help of family or village labor. Its net annual income[4] is approximately US$ 365.[5] Usually, the farmers keep a small fraction of the final crop output for personal consumption and sell the rest to licensed intermediaries in a government-regulated marketplace (known as a *mandi*).

Thus, the institutional setting is composed of three economic markets: (i) a market for intermediate inputs for farming; (ii) the regulated market where farmers sell their output to government-licensed intermediaries; and (iii) the retail markets where the intermediaries sell. The focus of my analysis is the regulated market and the transaction between the farmer and the intermediary.

Trade in agricultural commodities in India was regulated by two key laws, the Essential Commodities Act (1955) of the central government, which prohibits hoarding and free movement of produce across state lines, and the autonomous state-level APMC Acts. The APMC Acts mandate that sale and purchase of agricultural commodities produced in the state must be carried out in government-designated marketplaces, and buyers of agricultural output must obtain a license from the marketing committee of the marketplace. Thus, these acts restrict the set of buyers of farmers' output to intermediaries in the state (Chand 2012). Thereby these laws also reduce competition between marketplaces across state borders and provide a source of variation that can be exploited to estimate gains from increasing competition in the presence of spatially varying market power.

3. Agriculture Statistics at a Glance 2016, Ministry of Agriculture & Farmers Welfare, Government of India (2016).

4. Includes personal consumption valued at market prices.

5. Economic Survey of India, Ministry of Finance, Government of India (2016).

Movement of agricultural produce across state borders requires a document, called the *mandi parchi*, which certifies that the first sale occured at a state-regulated market place. This facilitates enforcement of border restrictions to movement of produce.[6] This does not preclude all leakages, but it is well understood in public policy debates that this restriction hurts farmers and scholars have called for repealing these laws (Patnaik and Roy 2019). Moreover, the central government has been trying to push the state governments to reform these laws.[7] However, these efforts have had little success.[8]

The most heroic attempt was made in the summer of 2020, when the central government, using COVID-19 as a pretext, tried to push through multiple reforms on agricultural marketing. This was hailed as the "1991 moment" for Indian agriculture by many economists (Gulati 2020). Since agriculture marketing is a state subject under the constitution, several states resisted it as they argue that the center stepped into their jurisdiction. Moreover, the reform package has created fears of potential corporatization of Indian agriculture. Thus, it was met with protests from several quarters, and the government had to roll it back.[9]

As such, as of today the regulated markets are the most important institutions for determining farmer incomes in India. My analysis ends in 2014, when the regulations of the laws described above was in force. These laws create licensed intermediaries who have monopsony rights over the farmers' output in the state. An intermediary has a license to a particular marketplace. Although multiple licenses are given per market, only a few are active and cartelization among intermediaries is common. Incumbent intermediaries also prevent new entrants (Chand 2012). Once an intermediary has bought crops from farmers, he moves them up the supply chain and sells them to a large miller or in the retail

6. While interning at the Office of the Chief Economic Advisor of India in 2015–16, I interviewed senior bureaucrats at the Ministry of Finance, the Ministry of Agriculture, and in three state governments (Punjab, Karnataka, and Madhya Pradesh) to understand the functioning of agricultural markets and the implementation of the laws.

7. See, Bera (2014) and Express News Service (2015), which describe how the current cross-border restrictions hurt farmers and the efforts of the central government to ameliorate them.

8. For details, see Sharma (2016).

9. See Bera (2020) and Sharma (2021).

markets. There are no legal restrictions on where the intermediaries can sell.

Given the importance of the regulated markets and the APMC Acts, I present a brief history of them next.

II.B. The Mandi Institution: A Brief History

The idea of the regulated agricultural marketplace in India has its genesis in a 1928 report by the British colonial government's Royal Commission on Agriculture in India. The chairman of this commission, Lord Linlithgow, had presided over a similar committee in 1922 that was supposed to investigate and comment on the "prevailing legal chaos" that raged around British agricultural markets. Four years later, in 1926, Linlithgow brought many of his unimplemented ideas derived from the British markets to his new job in India (Harris 1984; Krishnamurthy 2011). In his comprehensive report, he declared that the countrywide establishment of regulated markets "would confer an immense boon on the cultivating classes of India" (Royal Commission on Agriculture in India 1928).

This idea made sense at that time. Without any regulatory oversight, traders would often cheat farmers by using faulty weights or reneging on payments. Regulated market sites gave the authorities the power to discipline trading practices—implementing a standard system of weights and measures, enforcing timely settlements of trade, and providing other redress mechanisms to farmers. In an era, when information dissemination was very difficult, these regulated markets also became sites for information exchange (Krishnamurthy 2014). This idea was entrenched in the postcolonial policy for agricultural development, and regulated markets were seen as key to helping farmers realize a reasonable price in an environment where private trade was underdeveloped and controlled by mercantile power. Therefore, when the constitution of independent India gave legislative powers regarding agriculture to the states, each state adopted its own APMC Act in the 1960s and this restricted the first sale and purchase of crops in the boundaries of the states.

Under the aegis of the APMC Acts, new markets were created, especially during the Green Revolution that started in the mid-1970s, when agricultural production started increasing exponentially. Between 1976 and 1991, agricultural production grew

by 74%, and there was a concomitant 76% increase in the number of markets.

Over time, the incumbent traders began colluding and prevented new traders from entering the markets. The states reduced public investments in these markets, and the construction of *mandis* plummeted since the late 1990s. In fact, since 2001, very few new markets have been constructed (Chand 2012).[10] Hence, a regulation that was meant to benefit farmers became extractive over time (Chatterjee and Mahajan 2021).

II.C. Geographical Placement of Markets

Most of these markets were constructed between 1960 and 1985, during the peak of the Green Revolution in India, when grain production increased exponentially. According to the senior bureaucrats I interviewed in the state and central ministries of agriculture, historically, more markets were created in regions that had a greater yield or output per capita. In Online Appendix B, I verify that controlling for size, cropped area, and population of districts in 1970–85, the more productive districts have more markets today.

III. Data

Geospatial data on the location of markets and prices of commodities sold in them is necessary to assess the importance of spatial competition between intermediary traders for price determination. To capture the demand side, this should be matched geographically to local retail markets and must capture the local distribution of the population and retail prices. Furthermore, credible quantification of production losses requires fine geospatial data on land productivity, land use, rainfall, and crop choice. Because such a data set is not publicly available, I have assembled a rich and novel microdata set for India covering the decade of 2005–14 by combining data from various sources.

10. In my data set, I do not observe the year of construction or age of a market. As such, I will assume that in my sample period the number of markets is constant. Chand (2012) reports the aggregate growth rate of markets after 2001 to be 0.7%, and hence this will not be a major concern for me.

III.A. Intermediary Markets

My main data set is composed of monthly data on the modal price of eight major nonperishable commodities,[11] specifically rice, wheat, maize, sorghum, barley, pearl millet, finger millet, and soybean, sold in any regulated rural agricultural market, along with the village names of the market. This is the price which farmers get when they sell in these markets. I obtained this from the Ministry of Agriculture in India. I use Google Maps API to geocode the location of these markets.

I combine this with data on retail prices and production. These data are available only for administrative districts of India. There are 455 districts in the sample I consider, so they can substantially capture the spatial heterogeneity.

III.B. Retail Prices

I use monthly data on retail prices at the district level from the National Sample Survey (NSS) Schedule 3.01(R), Rural Price Collection Survey (RPC) survey of the Central Statistical Organization of India. These data are collected from a fixed set of 603 villages spread across India and are available for 2005–11, except 2008.

III.C. Production and Yields

To understand the cropping patterns of a district, I use data from the NSS Schedule 33, Situation Assessment Survey of Agricultural Households (Round 70) 2013. This is a large survey of rural agricultural households conducted twice a year, once in each cropping season, in 4,529 villages covering 35,000 households. Because the survey is representative at the district level, it provides a good estimate of the local cropping patterns.

11. These are producer prices, that is, the price that a farmer receives. The Indian government also has a Minimum Support Price (MSP) program and announces the procurement prices for 26 crops prior to the start of an agricultural season. Although legally the government promises to buy farmers' output at the announced MSP whenever market price falls below it, the reality is far removed. The MSP is only implemented for rice and wheat, and most procurement occurs in two states, Punjab and Haryana. Even in these states, the government actually relies on the intermediaries to procure the crops (Chatterjee and Kapur 2017). Online Appendix Figures K.1–K.10 plot the distribution of log prices alongside the MSPs for the crops. There is little evidence of price heaping just at or above the MSPs, as well as substantial mass below MSPs, suggesting that any biases from excluding MSPs from the model are limited.

In addition, I use estimates of the price elasticity of demand from Deaton (1997) and local crop yields at the district level for 2005–14 provided by the Ministry of Agriculture of India.

I further match the data on prices, production, and consumption with finer data on land use, land elevation, local distribution of population and their expenditure on food crops, local density of farmers and agricultural intermediaries, and the local availability of storages and warehouses. In particular, I obtained gridded data on land use from Princeton University's Geospatial Information Systems library and gridded data on land elevation produced by NASA's Shuttle Radar Topography Mission (SRTM) (National Aeronautics and Space Administration and the National Geospatial Intelligence Agency 2000). Gridded data on rainfall are from Willmott and Matsuura (2001). I compute district-level monthly rainfall by taking an inverse-distance weighted average of all the grid points in the boundary of any district.

Geocoded data on village population and farmers come from the census of India 2001, made available by NASA's Socioeconomic Data and Applications Center (Meiyappan et al. 2018). To compute local expenditures on food, I first estimate the per capita monthly consumption expenditure (MPCE) from the NSS Schedule 1.0, Household Consumer Expenditure Survey (Round 68) 2011. To obtain total expenditures at the subdistrict (*tehsil*) level, I multiply the MPCE by the local population of the subdistrict. To compute the total expenditure on food near any market, I aggregate up expenditures in all subdistricts within 30 km of that market.

Data on the number of traders at the district level is from the Economic Census of India 2005. Gridded data on local availablity of storages and warehouses come from the Online Management, Monitoring, and Accounting System of the Pradhan Mantri Gram Sadak Yojana, Ministry of Rural Development, Government of India.

III.D. Sample

For my analysis, I exclude the mountainous states of India because of the difficulty in measuring distances. I exclude Bihar and all northeastern states because they do not have an APMC Act, and there are no data on market-level prices. I also exclude some other territories and islands where agriculture is not practiced on any substantial scale. Therefore, my sample includes 15 states in mainland India covering 89% of the total cropped area

TABLE I
SUMMARY STATISTICS

	Mean	C.V.
Log farmer prices (Rs/kg)		
Barley	1.84	0.09
Finger millet	1.69	0.13
Maize	1.74	0.10
Paddy	1.80	0.12
Pearl millet	1.74	0.11
Sorghum	1.89	0.14
Soybean	2.46	0.03
Wheat	2.05	0.07
Log retail prices (Rs/kg)		
Barley	2.21	0.06
Finger millet	2.27	0.09
Maize	2.17	0.08
Paddy (rice)	2.61	0.06
Pearl millet	2.20	0.08
Sorghum	2.33	0.11
Soybean	3.13	0.13
Wheat	2.41	0.07
Std. dev. comp (as defined in equation (1))	1.58	

Notes. Coefficient of variation of log prices is computed across districts, within an agricultural season. Years are restricted to those for which the data on both retail and farmer prices is available.

and accounting for 90% of total production. The states are shown in Online Appendix A. In my data set, this results in a total of 2,978 primary grain markets.

Table I presents summary statistics on prices at the market and retail levels.

IV. DOES MORE SPATIAL COMPETITION INCREASE FARMERS' PRICES?

The analysis in this section is focused on the regulated marketplace where the transaction between the farmer and the government-licensed intermediary occurs.[12] There are two potential forms of local competition among buyers (i.e., the licensed intermediaries in markets): between and within market sites. In this article, I focus on between-market (or spatial) competition[13]

12. See Section II.A for a discussion of the overall economic environment of agricultural trade in India.

13. Here, spatial competition is defined by geography and regulation rather than the (endogenous) number of firms in a market and those nearby.

because current empirical evidence suggests that intermediaries in a market collude.[14] This section provides two forms of reduced-form evidence that suggest (i) spatial competition between market sites increases prices that farmers get for their output (hereinafter farmer prices); and (ii) state borders attenuate competitive forces, that is, the presence of more markets in the neighboring state does not influence farmer prices.

The hypothesized mechanism influencing farmer prices, which will be explicit in the quantitative model, hinges on a farmer's access to alternative buyers while negotiating with a buyer at a given market site. More markets in the vicinity increase the set of alternatives available to the farmer, increasing the competition faced by the present buyer. Consequently, the farmer is likely to be offered a better price. Therefore, greater competition is likely when alternative markets are closer and there are more of them. Moreover, since the APMC laws require farmers to sell their crops within the state's borders, more markets in a neighboring state should not have an influence on farmer prices. I test for these implications below.

IV.A. Effect of Within- and Out-of-State Competition

To explore the association between spatial competition and farmer prices, I regress farmer prices at a particular market site on a measure of local market density (or spatial competition faced by a market). Similar to the market access measure in Harris (1954) and Donaldson and Hornbeck (2016), I construct a local spatial competition measure by taking a weighted sum of other markets near a particular market site but in the same state. The weights are the inverse of distances of the neighboring markets to the origin market.[15] For any market m,

$$\text{(1)} \qquad \text{comp}_m = \sum_{j \in \mathcal{M} \setminus \{m\}} \left\{ \frac{1}{\text{distance}_{mj}} \right\} \mathbb{1} \left\{ \text{state of } m = \text{state of } j \right\}.$$

$\mathcal{M}$ is the set of all markets in the country. As competition (in any market m) is driven by a farmer's ease of access to alternative

14. See Banerji and Meenakshi (2004) and Meenakshi and Banerji (2005).

15. Donaldson and Hornbeck (2016) compute a weighted average of the total trade in a market. I do not have data on trade and therefore do not compute the trade-weighted measure. However, the number of proximate competitors, as a measure of competition, has also been used by Macchiavello and Morjaria (2021).

markets, the comp_m measure assigns a greater weight to a closer market. I also create an analogous competition measure for a market site from the markets not in the same state. Under the null hypothesis, this measure should have no association with prices received by farmers at any market site:

$$\text{comp}'_m = \sum_{j \in \mathcal{M} \setminus \{m\}} \left\{ \frac{1}{\text{distance}_{mj}} \right\} \mathbb{1} \{\text{state of } m \neq \text{ state of } j\}. \tag{2}$$

My main specification takes the following form:

$$\begin{aligned} \log p^f_{cmdst} = {} & \beta_0 + \beta_1 \text{comp}_m + \beta_2 \text{comp}'_m + \mathbf{X}'_{cdt}\beta_3 + \gamma_t \\ & + \gamma_c + \gamma_s + \epsilon_{cmdt}. \end{aligned} \tag{3}$$

Here, p^f_{cmdst} is the price that a farmer receives at market site m in district d, state s, for crop c, at time (month-year) t. All price observations are at market-crop-month level. $\mathbf{X}$ includes controls for district-specific time (year) varying controls like crop yields, crop area, population, and rainfall shocks. Since rainfall sensitivity may vary across crops, rainfall shocks at the district level are interacted with crop dummies. γ_t is a month-year fixed effect and controls for crop- and district-invariant unobservables such as macroeconomic shocks, large-scale droughts, and so on. γ_c controls for crop-specific factors such as crop-specific price levels and national tastes for particular crops. γ_s controls for state-specific and crop-time invariant effects such as state-level policies, relative incomes of states, and local tastes. Since cropping decisions and other shocks are likely to be spatially and serially correlated, I compute robust standard errors clustered at the district level.

Variation in comp_m comes from geographical differences in the placement of markets. Because the local crop production to population ratio drives this variation, I control for local yields, local cropped area, and population in regression (3). β_1 is identified from within-state variation in comp_m under the assumption that comp_m is uncorrelated with the residuals. As very little *mandi* construction occurred in my sample period, and I do not have data on the date of construction of markets, comp_m does not vary over time. Therefore, threats to identification can come only from spatially varying factors, and I have tried to control for as many of them as possible. I have not included district fixed effects because there are very few markets in a district, and therefore I do not

have enough within-district variation in spatial competition to identify its effect on prices.

Within-market competition is an omitted variable in all my regressions and can potentially confound my estimates if markets in local areas with a greater market density also have greater within-market competition. In the absence of any data on the number of buyers within a market or their transactions, I cannot control for it directly. However, I try to address this lacuna by controlling for several measures that could potentially be correlated with the degree of within-market competition or the local bargaining ability of farmers. First, I control for the number of agricultural traders and commission agents in the district. While this measure is not exactly the same as the number of licensed traders in any market-site, it does provide a reasonable estimate of the local supply of agricultural intermediaries in the district and thus the degree of local within-market competition. Second, it is also reasonable to expect that the local bargaining ability of the farmers at a market (or the within-market competition) is correlated with the number of farmers present there.[16] Thus, I control for the density of farmers in a 30 km radius around any market. Third, the relative bargaining power of farmers vis-à-vis intermediaries could also be influenced by availability of storage infrastructure, as that might increase the holding capacity of either party. Therefore, I control for the local availability of cold storages and warehouses in a 30 km zone near each market. As we will see, the results are robust to these controls. This is not entirely surprising given that the existing evidence suggests that collusion among traders within a market is usually very high (Banerji and Meenakshi 2004; Meenakshi and Banerji 2005). Furthermore, there is evidence that incumbent traders have actively tried to prevent entry of new traders (Chand 2012).

Table II reports the regression results. Column (1) reports results from the base specification given in equation (3). The coefficient on competition, β_1, is significant and equals 0.0163. In column (2), I include crop-time fixed effects, which control for monthly world price shocks, and state-year fixed effects, which control for state-specific income levels and policy changes that vary over time. This does not change the estimate of β_1 much, which now equals 0.0146 and is still significant. The coefficient

16. I thank an anonymous referee for this suggestion.

TABLE II

PRICES AND LOCAL COMPETITION

Dep. variable:	Log farmer price						Log retail price			
	All markets				Border markets		Agricultural products		Tradable goods	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
comp (β_1)	0.0163	0.0146	0.0154	0.0137	0.0322	0.0292	– 0.0107	– 0.0099	– 0.0091	– 0.0090
	(0.0074)**	(0.0073)**	(0.0077)**	(0.0078)*	(0.0234)	(0.0226)	(0.0102)	(0.0094)	(0.0094)	(0.0094)
comp' (β_2)	– 0.0005	– 0.0007	– 0.0006	– 0.0003	– 0.0057	– 0.0056	0.0071	0.0060	0.0056	0.0057
	(0.0020)	(0.0019)	(0.0019)	(0.0019)	(0.0076)	(0.0075)	(0.0046)	(0.0046)	(0.0035)	(0.0036)
Local population	0.0180	0.0113	0.0107	0.0047	– 0.1045	– 0.0909				
	(0.0675)	(0.0633)	(0.0626)	(0.0631)	(0.0979)	(0.0822)				
Log(farmers)			– 0.0001	– 0.0012						
			(0.0068)	(0.0068)						
Log(intermediaries)			0.0027	0.0024						
			(0.0031)	(0.0031)						
Log(storages)				0.0048						
				(0.0036)						
Log(warehouses)				0.0007						
				(0.0030)						
$\beta_1 - \beta_2$	0.0169	0.0154	0.0160	0.0140	0.0381	0.0348				
	(0.0072)**	(0.0071)**	(0.0075)**	(0.0075)**	(0.0224)*	(0.0218)				
Observations	211,963	211,954	211,954	211,954	15,838	15,751	52,857	52,856	8,583,630	8,583,630
R-squared	0.60	0.68	0.68	0.68	0.57	0.68	0.74	0.78	0.93	0.93
State, crop FE	√				√		√		√	
Month-year FE	√				√		√		√	
State-year FE		√	√	√		√		√		√
Crop-month-year FE		√	√	√		√		√		√

Notes. Ordinary least squares. Each observation is a crop-market-month-year. All regressions include controls for district-year specific crop yields, crop area, and crop-specific rainfall shocks. Local population is a distance-weighted population average in the 30 km zone around each market. The coefficient on local population has been multiplied by 100. Columns (5) and (6) contain only those markets that are within 30 km of state borders. This sample is the same as in Table III, columns (3) and (4). Columns (9) and (10) are regressions for 117 tradable nonagricultural goods like shirts, sarees, hair-oil, and toothpaste, instead of crops, and therefore crop fixed effects are replaced with product fixed effects. Robust standard errors clustered at the district level are reported in parentheses. Crops in the sample are barley, finger millet, maize, paddy, pearl millet, sorghum, soybean, and wheat. $^{*}p < .1$, $^{**}p < .05$, $^{***}p < .01$.

on out-of-state competition β_2 is close to zero and not significant in both columns. In columns (3) and (4), I control for various measures of local within-market competition like the local supply of traders, local farmer density, and local availability of storages and warehouses, and the main result is robust to inclusion of these controls. Finally, one could expect that economies of scale vary by crop. The results (not reported) are robust to interacting crop area with crop dummies.

The key message is that greater local spatial competition increases farmer prices. A one standard deviation increase in competition increases prices by 2.7%. Moreover, the competition from markets in other states has no effect on prices. To get a sense of the overall magnitude of gains, note that if we removed all border restrictions to trade, the median increase in competition would be 1.6 standard deviations. This would increase prices in half the markets in India by at least 4.4%.

IV.B. Causal Effects of Spatial Competition on Prices

Although the previous regression design shows that spatial competition increases farmer prices and borders reduce out-of-state market competition, one can still be concerned about other forms of unobserved heterogeneity. Therefore, to test this idea more concretely, I implement a border discontinuity design with market pairs. I match all markets that are less than x km apart but lie on different sides of a state boundary. Here, $x = 25$, 30, and 35. I regress the difference in prices for each market pair on the difference in their competition measures.

The basic idea is that other determinants of prices like demand, productivity via soil quality, and rainfall vary continuously across a state boundary. Indian state boundaries were primarily determined along linguistic or cultural lines rather than geography (Guha 2007). Thus, the only determinant of prices that changes discontinuously across state borders is local competition because farmers are not allowed to sell their output in the markets of other states.[17] Therefore, along a state boundary, the correlation between the difference in prices and the difference in market density between market pairs should help us identify causal effects of local competition on prices.

17. Indian languages change very gradually over distance. Therefore, it is not the case that farmers in one state will not be able to communicate with farmers or intermediaries in the neighboring state.

In the previous design, since I relied on within-state variation for identification, I could not fully address concerns about unobserved heterogeneity. The advantage of this design is that I can difference out unobserved factors other than spatial competition that affect prices by choosing market pairs very close to each other.

I start with a levels specification as in equation (3) and then take a difference between all market pairs $(m - m')$ that are within the selected bandwidth but lie in different states.

$$\log p^f_{cmdt} = \beta_0 + \beta_1 \text{comp}_m + \gamma_t + \gamma_c + \gamma_s + \epsilon_{cmdt},$$

$$\Delta \log p^f_{cmdt} = \beta_1 \left(\Delta \text{comp}_m\right) + \gamma_{ss'} + \tilde{\epsilon}_{cmt}. \tag{4}$$

β_1 is the causal effect of spatial competition on prices. $\gamma_{ss'}$ is a border fixed effect, specific to two states sharing a common border. This specification controls for unobservables like differences in state-specific policies, law enforcement, and tax regimes that do not vary along the common border but might potentially differ across state pairs. Because the market pairs are very close to each other, shocks can be spatially correlated. I report (in square brackets) standard errors corrected for spatial correlation.

Following Conley (1999), I allow for spatial dependence of an unknown form within a 100 km surface from the midpoint of the line segment joining the market pair. To be more precise, the variance-covariance matrix is estimated as a uniformly weighted sum of cross-products of the OLS moments ($E[x_i \epsilon_i] = 0$). For comparison, I also report OLS standard errors in parentheses.[18]

I report the results in Table III. The preferred estimates are reported in column (4), which has a bandwidth of 30 km. The marginal effect of competition on prices, β_1, equals 0.035. Choosing bandwidths lower than 25 km reduces the number of market pairs and then I do not have enough power to precisely estimate the effect of competition on prices. As reported in Table III, column (1) where the bandwidth is 25 km, β_1 is equal to 0.025 but is not precisely estimated. Also, as can be seen from column (7),

18. I am restricted to computing cluster robust standard errors for the levels specification (3) because of the computational burden of computing Conley (1999) standard errors.

TABLE III

BORDER DISCONTINUITY REGRESSIONS

Dep. variable:	Δ log price								
	Markets < 25 km apart			Markets < 30 km apart			Markets < 35 km apart		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Δ comp (β_1)	0.025	0.034	0.030	0.035	0.036	0.035	0.036	0.027	0.024
	[0.015]	[0.016]**	[0.015]**	[0.016]**	[0.017]**	[0.017]**	[0.012]**	[0.013]**	[0.012]**
	(0.011)***	(0.012)***	(0.012)***	(0.010)***	(0.010)***	(0.010)***	(0.009)***	(0.009)***	(0.007)***
Obs	3,538	3,538	3,538	5,292	5,292	5,292	9,018	9,018	9,018
Market pairs	108	108	108	173	173	173	284	284	284
Controls:									
State-pair FE	√	√	√	√	√	√	√	√	√
Δ farmers		√	√		√	√		√	√
Δ traders			√			√			√

Notes. Observations are market-pair-crop-month. Square brackets contain Conley (1999) standard errors that allow for spatial and serial correlation of the error terms. Arbitrary spatial correlation in error terms is allowed within 100 km from the geographic midpoint of the market pairs. Serial correlation is allowed over six months, equivalent to one crop season in India. OLS standard errors are reported in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$.

the estimate of β_1 settles down to about 0.035 as we increase the bandwidth further.[19]

Like before, there is a positive effect of local competition on farmer prices. However, the effect size is almost double compared to the estimate of 0.016 from the levels specification reported in Table II. This is most likely because the true relationship in the data is probably nonlinear, and the border regressions concentrate the variation in the steeper part of the relationship. To verify this, I estimate the levels specification (3) but restrict the sample to just those used in the border regressions. The results for the markets in the 30 km bandwidth are reported in Table II, columns (5) and (6). As expected, for this smaller sample, the OLS estimate of β_1 is about 0.03.

Restricting the sample to just those markets close to the borders provides another way to estimate the causal effect. In the OLS specification (3), β_1 could be biased if it is correlated with other omitted factors that also affect prices. However, when I limit the sample to markets very close to all state borders, then these omitted factors are likely to affect comp'_m in a manner similar to their effect on comp_m. Therefore, $\beta_1 - \beta_2$ should help us identify the "true" competition effect as β_2 (the coefficient on comp'_m in equation (3)) purges β_1 from any contamination. I report these results in the last row of Table II, columns (5) and (6), where we indeed find that the estimated effect of 0.038 is almost identical to that obtained from the border regressions.

As per these results, a farmer selling in a market that faces the 75th percentile of competition compared to one that faces the 25th percentile of competition gets a 3.5% higher price on average. A one standard deviation increase in competition would lead to a 6.4% increase in price on average.

1. *Threats to Identification.* There could be several threats to the identification of the border regression (4). These could result from omitted variables that change discontinuously at the state borders and vary systematically with the spatial competition measure along the borders. The first threat comes from more markets being placed in historically more productive regions (see Section II.C). The aim of the border regression design is to control for such differences by focusing on markets very close to each

19. Note that my choice of bandwidths is much smaller than similar border discontinuity designs, such as Dell (2010).

other. In Online Appendix C, Panels A and B, I present placebo tests to show that there are no discontinuities at state borders in potential crop productivities and land elevation that might influence prices.

A second threat could come from the fact that unobservably more productive farmers can cross the border into more competitive regions.[20] This may well be possible if the laws are imperfectly implemented. Without any data on the identity of farmers, it is impossible to test this directly. However, the fact that in the levels regressions (3) the out-of-state competition measure is not statistically different from zero gives some evidence that such instances are not very common. Furthermore, to the extent that such border crossing may happen to some degree anyway, it should equalize price gaps on both sides of the border as crop supply increases in the more competitive regions. Because this would reduce the effect size, my estimates should be interpreted as a lower bound.

The third threat would come from the degree of unobserved within-market competition varying systematically with spatial competition along the state border. As I discussed already, this could be because more markets are correlated with more intermediaries, farmers, or availability of agricultural infrastructure, all of which could influence the relative bargaining ability of farmers. In Online Appendix C, Panels B and C, I show that the availability of cold storages, warehouses, and the supply of intermediaries do not vary systematically with the competition measure along state borders. However, the density of farmers near a market does correlate positively with market density. This is to be expected because these markets were historically placed in regions with more production. More people in subsequent generations could have chosen to become farmers in these regions. To check that such differences in farmer density that vary discontinuously at the border do not influence the prices that farmers receive, I explicitly control for it in the border regressions (4). These results are presented in Table III, columns (2), (5), and (8). Not only is the main effect of spatial competition on prices stable at 0.03, but the coefficient on farmer density is not statistically different than zero. The results are also robust to including the number of intermediaries as an additional control. This is in line with the results we had seen with the levels regression in Table II. These checks should give us more

20. I thank an anonymous referee for highlighting this potential threat to identification.

confidence in the assumption that the degree of within-market competition does not vary systematically with spatial competition and that the regressions are recovering unbiased estimates of the effect of spatial competition on farmer prices.

A final story that needs to be ruled out is that of market access. Even though there is no institutional restriction on consumers moving across state borders, if consumer expenditure is greater in regions with more agricultural wholesale markets, then farmers could be getting higher prices simply because of higher demand for their products.[21] To allay these concerns, I run the price regressions—both in levels and in the border specification—for retail instead of farmer prices. I do this separately for two sets of products: first, the agricultural commodities in my base sample, and second, 117 tradable consumer products like hair oil, toothpaste, shaving cream, pens, pencils, shirts, and so on. The results for the levels specification (3) are reported in Table II, columns (7)–(10) and for the border regression (4) in Online Appendix C, Panel C, columns (2) and (3). The spatial competition measure does not seem to affect retail prices for either agricultural goods or consumer products. Furthermore, since demand could discontinuously vary at state borders because of unobserved border effects, I run direct placebo tests for local food expenditure near agricultural markets. This result, reported in Online Appendix C, Panel C, column (1), suggests that spending by people on crops does not vary systematically with market density along state borders. All these placebo tests increase the credibility and the confidence that the underlying mechanism driving the relationship between farmer prices and market density is more likely to be spatial competition than market power.

To summarize, I provided evidence for two aspects of spatial competition between intermediary markets. First, local competition, determined via density of markets, matters for farmer prices. Second, border restrictions have real effects in that they nullify the competitive forces from markets in neighboring states. As such, the quantitative effects of increased competition on prices, agricultural output from an induced change in use of intermediate inputs, and other welfare measures can be large if border restrictions on trade are removed. With farmers being able to freely cross state boundaries, not only does competition increase among

21. I thank an anonymous referee for pointing out this potential mechanism and suggesting ways to empirically rule it out.

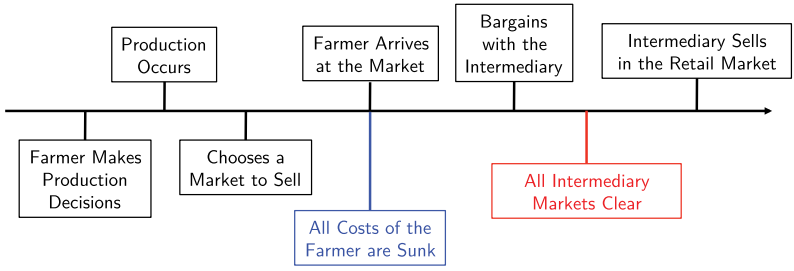

FIGURE I

Timing of Events

markets at the border but also potentially throughout the country via a ripple effect—since a price increase in one market influences the prices in adjacent markets and so on—and therefore competition affects prices even in the interior markets.

Quantification of such ripple effects needs the aid of a spatial model of trade that uses the location of markets and the economic geography of the country and allows farmers to remove price arbitrages in space. In the next section, I set out such a model. In the baseline, I limit the choice set of farmers to be the markets only in their own state and expand this to be any market in the country in the counterfactual.

V. MODEL

I develop a simple model of trade in agricultural markets in India that will flexibly capture the forces of spatial competition between markets and aid us in quantifying the income and productivity effects of border restrictions on trade. The basic structure of the model is as follows. The economy consists of many geographic regions. In each region there are two types of agents: farmers and intermediaries. Each intermediary is identified with a market. The location of markets is determined exogenously by the government. Each farmer first chooses input levels. After the realization of output, he chooses the market where he wants to sell his output. Transporting goods is costly. The price that a farmer receives at a given market is determined by Nash bargaining between the farmer and the intermediary after the farmer has arrived at the market with the output. Intermediaries sell all of the purchased output in the retail market at an exogenously given price. Figure I

shows the timing of events.

I provide formal details of the model next.

V.A. Setup

1. *Geography.* There are S regions in the economy. Regions in the model are analogous to the states of India. For now, and motivated by the regulatory structure in India that prohibits farmers from selling their output across different states, there will be no interactions between regions. In what follows, I focus on a generic region and abstract from indexing the region.

The region has two types of agents: F farmers and M intermediaries. $\mathcal{F}$ and $\mathcal{M}$ are the sets of all farms and intermediaries in the region, respectively. Each farmer f is identified by a given plot of land, or farm, and each intermediary m is identified by a specific market. Farms and markets are distributed in space, so I also refer to f and m as locations. Geography matters because it is costly to move goods across locations. I model these costs as iceberg trade costs and denote by $\tau_{xy}(>1)$ the amount of goods that must be moved from location x for one unit to arrive at location y.

2. *Farmers.* There is a single crop in the economy.[22] Land and labor available to a given farm are fixed and denoted by h_f and l_f, respectively.[23]

A farmer purchases $\{x_f^k\}_k$ units of K intermediate inputs and his output is given by:

$$y_f = \tilde{A}_f \left(h_f^{\gamma} l_f^{\nu} \prod_{k=1}^{K} \left(x_f^k\right)^{\alpha_k} \right),$$

$$\sum_{k=1}^{K} \alpha_k + \nu + \gamma = 1; \alpha_k > 0 \, \forall k, \;\; \nu, \gamma > 0. \tag{5}$$

$\tilde{A}_f$ is the total factor productivity for farm f. The market for inputs is perfectly competitive. w^k, the price of the kth input, is the same

22. I incorporate multiple crops later but continue to treat crop choice as exogenous.

23. This is the farm of the median Indian farmer who owns about 1.5 ha of land (Ministry of Finance, Government of India 2016) and mostly uses family or village labor for cultivation. To the extent that large farmers in India may hire migrant labor, my estimates of gains in income and productivity should be thought of as lower bounds that ignore adjustment in the labor market.

for all farmers in the region and is exogenously given. Farmers are small compared to the input, output, and the retail markets and therefore cannot influence prices directly.

3. *Market Choice.* Upon harvest, farmers optimally choose the market where they want to sell. Because farmers are subject to iceberg trade costs, the quantity of output actually reaching any market m from farm f is

$$q_{fm} = \frac{y_f}{\tau_{fm}}. \tag{6}$$

The price that farmers would get in market m is denoted by $p^f(m)$. Thus, farmers choose market m to sell their output such that their income $\frac{p^f(m)y_f}{\tau_{fm}}$ is maximized.

4. *Price Determination and Intermediaries.* Once a farmer f reaches a market m with his goods, all his costs are sunk. He bargains with the intermediary associated with market m over the price for a unit of his output. The outcomes are determined via Nash bargaining. The outside option of the farmer, $\underline{p}(m)$, is the value that he would receive by going to the best alternative market. The best alternative is given by,[24]

$$\underline{p}(m) = \max_{k \in \mathcal{M} - \{m\}} \left\{ \frac{p^f(k)}{\tau_{mk}} \right\}. \tag{7}$$

The outside option for the intermediary is zero. If an intermediary m purchases q units of output from a farmer, he will sell this on the local retail market and receive a price p^r_m for each unit of output. A local retail market is the Indian administrative district in which the market is located. Each market is small compared to

24. In Online Appendix H.2, I discuss the sensitivity of my results to an alternative formulation where the outside option is "smoother" because farmers have idiosyncratic preferences to go to certain markets. In particular, these taste shocks are drawn from a Fréchet distribution with scale parameter 1 and shape parameter θ. Then, $\underline{p}(m) = \Gamma \left(\sum_{k \neq m} \left(\frac{p^f(k)}{\tau_{mk}} \right)^{\theta} \right)^{\frac{1}{\theta}}$, where Γ is a constant.

the local retail market and therefore the intermediary takes the retail price as given.[25]

If δ denotes the bargaining weight for the farmer, the Nash-bargaining outcome is the solution to:

$$\max_{\lambda} \left(\lambda - \underline{p}(m) q_m\right)^{\delta} \left(p_m^r q_m - \lambda\right)^{1-\delta}. \tag{8}$$

Here, λ is the farmer's income. Since $p_m^r q_m$ is the total surplus, $p_m^r q_m - \lambda$ is the income of the intermediary trader from this transaction. Note that all farmers trading at a particular market m receive the same price because what matters is the distance of the next-best alternative from a particular market and not the distance to that farmer's farm. Therefore, I omitted the subscript f in the bargaining problem.

5. *Equilibrium.* To solve for the spatial equilibrium, I employ the Nash-in-Nash (à la Horn and Wolinsky 1988) solution concept—the price negotiated at a market will be the Nash-bargaining solution given that farmer-trader pairs in all other markets reach an agreement. The equilibrium for a region S is defined as follows:

DEFINITION 1. Given parameters $\{\alpha_k\}_{k=1}^{K}$, ν, γ, and, δ, endowments $\{h_f, l_f, \tilde{A}_f\}_{f\in\mathcal{F}}$, transportation cost function τ, and retail and intermediate input prices $\{p_m^r\}_{m\in\mathcal{M}}$ and $\{w^k\}_{k=1}^{K}$, respectively, an equilibrium is a set of farmer prices $p^f(.)$, intermediate-input choices $\{x_f^k\}_{k\in\mathcal{K}, f\in\mathcal{F}}$, and the optimal market choice at each farm, denoted by $\{\mu(f)\}_{f\in\mathcal{F}}$, such that:

i. Farmers choose intermediate inputs to maximize their profits, to solve:

$$\max_{\{x_f^k\}_k} p^f(\mu(f)) \tilde{A}_f \left(h_f^{\gamma} l_f^{\nu} \prod_{k=1}^{K} \left(x_f^k\right)^{\alpha_k}\right) - \sum_{k\in K} w^k x_f^k. \tag{9}$$

25. For the main analysis, I read local retail prices from the data. In Section VII.D, I endogenize retail prices and let them adjust in response to changes in local supply.

ii. Farmers optimally choose a market to sell their output, according to:

$$\mu(f) = \arg\max_{m\in\mathcal{M}} p^f(m) q_{fm} = \arg\max_{m\in\mathcal{M}} \left\{ \frac{p^f(m) y_f}{\tau_{fm}} \right\}. \tag{10}$$

iii. Farmers and intermediaries in any market Nash bargain over the total value of the farmer's output assuming that bargainers in all other markets have reached an agreement.

V.B. Solving the Model

We can now solve the model backward from the timeline in Figure I. Conditional on the retail prices that intermediaries get, we first solve the bargaining problem between the farmers and the intermediaries.

1. *Solution of the Bargaining Problem.* The solution of the bargaining problem (8) gives us:

$$p^f(m) = (1-\delta)\,\underline{p}(m) + \delta p^r_m, \tag{11}$$

where $p^f(m) = \frac{\lambda}{q_m}$.

We have one such equation for every market and all of them are interrelated through the outside option, $\underline{p}(m)$. Equilibrium farmer prices are then just the fixed point for the system of M equations in M endogenous variables defined in equation (11).[26]

THEOREM 1. Given retail prices $\{p^r_m\}_{m\in\mathcal{M}}$, there exists a unique fixed point $p^{f*}(.) : \mathcal{M} \to \Re_+$, that solves the system of equations given in equation (11).

The proof can be found in Online Appendix D. Intuitively, I can show that $p^f(.)$ is a contraction as $\delta \in (0, 1)$ and $\tau \geqslant 1$, and therefore there is a unique solution.

Once we know the equilibrium farmer price in any market $m \in \mathcal{M}$, denoted by $p^{f*}(m)$, the optimal market choice is given by equation (10). Subsequently, the input choices would be the

26. In the quantitative section, I assume the problem to be independent across crops and time periods. Therefore, the problem with all crops and multiple periods involves finding a fixed point of a system of $M \times C \times T$ equations in $M \times C \times T$ variables, where T is the number of time periods.

result of a standard profit-maximization problem (9), given the production function and intermediate-input prices.

LEMMA 1. Given retail prices, removing restrictions on farmers from trading across regions will improve the prices that they receive.

The formal proof of Lemma 1 is relegated to Online Appendix E; the main intuition is as follows. In the system of equations (11) that determine equilibrium prices, the only variable that changes in the counterfactual is the set of outside available options to the farmer. In particular, $\mathcal{M}$ will include all markets in India as opposed to markets in the region (or that state). As the local retail prices are held fixed and we are taking the maximum over all outside options, the prices they receive in equilibrium cannot be strictly lower than before.

Lemma 1 guarantees that as long as retail prices do not change, no farmer will be worse off as a result of the removal of trade restrictions. When farmers are allowed to trade across states, the degree of spatial competition between intermediary markets on both sides of the border increases, resulting in an increase in farmer prices in markets on both sides of the border. The only way farmers can lose in this setup is if, due to an increase in supply, the retail prices fall enough to lower the total surplus and thus the prices farmers receive in markets.

V.C. Demand in Retail Markets

To complete the model, I define the demand side here. Each region above is further divided into subregions, indexed by d. Each subregion corresponds to an Indian administrative district, as defined by law, and as discussed in Section V.A is the local retail market. The aggregate demand function for a subregion is given by

$$Q^d = Q\left(p_d^r\right). \tag{12}$$

Let η be the price elasticity of demand. I assume that the elasticity is constant with respect to Q^d. All intermediaries m located in subregion d sell in the same subregion and hence, $p_m^r = p_d^r \ \forall m \in d$.[27] Finally, for retail markets to clear, total quantity

27. This is an assumption. Equivalently, retail markets can be assumed to be perfectly integrated and then retail prices would differ across regions only due to

demanded in a subregion d must equal total quantity sold in that subregion

$$\sum_{f \in \{\mu^{-1}(m) | m \in d\}} y_f = Q^d. \tag{13}$$

VI. Estimating The Model

To take the model to data, I need to expand it to include multiple crops and time periods. Crops and time periods are assumed to be independent and therefore, in the quantitative section we will have $M \times C \times T$ equations of the form of equation (11), where C is the number of crops and T is the number of time periods. To quantify the gains from increased spatial competition due to removal of restrictions on farmers' trading across state borders, I structurally estimate the model presented in the previous section. First, I parameterize τ and then estimate δ and the parameters in the trade cost function jointly to match the spatial distribution of farmer prices. I conduct a sensitivity analysis to understand what features of the data inform the parameters. I set the production function parameters to match land and labor shares in my data and I take demand elasticities from the literature.

VI.A. Estimating τ and δ

I parameterize trade costs as a function of distance, and I estimate the parameters using data on the location of markets. I define the trade cost between two markets m and k, for crop c, and at time t as:

$$\tau_{mkct} = \begin{cases} 1 & m = k \\ 1 + A \cdot d_{mk} + \epsilon_{mct} & m \neq k \end{cases}, \tag{14}$$

$$\log \epsilon_{mct} \sim N(0, \sigma),$$

where, d_{mk} is the geodesic distance[28] between locations m and k and A is a scale parameter. The shock term, ϵ_{mct}, represents origin market crop-specific costs like broken roads, availability of a truck, or a strike among intermediaries, which are not observable to the econometrician but are known to the farmers. τ_{mkct} is set

transport costs. In the latter case, the intermediary will be indifferent between selling in different retail markets.

28. The shortest distance along the Earth's surface.

to infinity if markets m and k lie in different states to incorporate trade restrictions.[29]

If I denoted crops by c and time period by t, then the key equilibrium equation of model (11) becomes

$$p^f(m,c,t) = (1-\delta) \max_{k \in \mathcal{M}-\{m\}} \left\{ \frac{p^f(k,c,t)}{1 + A \cdot d_{mk} + \epsilon_{mct}} \right\} + \delta p^r_{mct}. \tag{15}$$

From equation (15), we can see that prices in the different markets are interrelated. Therefore, the marginal likelihood function of price at one market is not independent of prices in the other markets. Hence, estimation cannot be carried out via a standard maximum likelihood or a method of moments procedure. To address this, I use a method of simulated moments procedure to estimate (δ, σ, A). In particular, I choose (δ, σ, A) to minimize the distance between moments of the data and their simulated counterparts.

Formally, the method of simulated moments chooses parameters $\Theta = (\delta, \sigma, A)$ to minimize the distance between simulated and data moments, solving:

$$\hat{\Theta} = \arg\min(\Psi^d - \Psi^s(\Theta))W(\Psi^d - \Psi^s(\Theta))',$$

where W is the optimal weighting matrix—the inverse of the variance-covariance matrix of the moments; Ψ^d are the data moments; and $\Psi^s(\Theta)$ are the simulated moments. I compute robust standard errors clustered at the state-season level and use numerical methods to find the required gradients.

1. *Choice of Moments and Estimation.* To identify moments that will inform the estimation, I choose an auxiliary regression model that mimics the equilibrium equation (15) as closely as

29. In Online Appendix H, I discuss the robustness of my results to the linear functional-form assumption of trade costs.

possible.[30]

$$\ln p^f_{mct} = \tilde{\beta}_0 + \tilde{\beta}_1 \left(\max_{k \in \mathcal{M}-\{m\}} \ln p^f_{kct} \right) + \tilde{\beta}_2 \log d_{mk^*} + \tilde{\beta}_3 \ln p^r_{mct} + \gamma_c + \xi_{mct}. \tag{16}$$

Here, p^f_{mct} and p^r_{mct} are the prices farmers get and the retail prices in market m for crop c at time t, respectively. d_{mk^*} is the distance from market m to market k^*, which has the highest price in the neighborhood, and γ_c is a crop fixed effect. I match five moments from the auxiliary regression: $\tilde{\beta}_0$, $\tilde{\beta}_1$, $\tilde{\beta}_2$, $\tilde{\beta}_3$, and the mean squared error of the auxiliary regression. In addition, I match the distribution of farmer prices using the mean and the variance of farmer prices, and the fraction of data in different parts of the distribution. Let us denote the kth percentile of the distribution of farmer prices in the actual data by pc_k, and simulated farmer prices by $\tilde{p}^f_{mct}$. Then the moment condition is defined as:

$$\psi(\Theta) = \mathbb{1}\left[\tilde{p}^f_{mct} \in \left[pc_k, pc_{k+\zeta}\right]\right] - \zeta,$$

where ζ is the chosen bin size. I use four bins: 5th–25th, 25th–50th, 50th–75th, and the 75th–95th percentiles. Hence, $\zeta = 0.2$ for the first and the last bin and 0.25 for the second and the third bin.

Although in principle all parameters are jointly estimated to match the distribution of prices, some moments are more important for identifying some parameters. Intuitively, the Nash-bargaining parameter, δ, is identified from the correlation between retail and farmer prices, $\tilde{\beta}_3$, and that between farmer price in a market and the maximum price in the neighborhood, $\tilde{\beta}_1$.

From equation (15), one can see that A, the scale parameter on distance, and σ, the variance of the shock term, matter for the level of prices. As $\tilde{\beta}_3$ is influenced by δ, and $\tilde{\beta}_1$ is influenced by

30. Following Gourieroux, Monfort, and Renault (1993), identification of the auxiliary regression is not necessary for consistent estimation of the structural parameters. It just needs to capture key moments of the data that can inform identification of the structural parameters. One reason not to use only the border regression (4) as an auxiliary model is that it does not capture the relationship between farmer prices, distances to other markets, and retail prices. These moments are important for identification of the model parameters. I use the nontargeted border moment for model validation instead.

δ, A, and σ, $\tilde{\beta}_3 - \tilde{\beta}_1$ has information about A and σ. Conditional on $\tilde{\beta}_3 - \tilde{\beta}_1$, $\tilde{\beta}_2$ helps separate A from σ. For example, if $\tilde{\beta}_3 - \tilde{\beta}_1$ is large, such that prices in the neighborhood are less important, then trade costs must be high. In addition, if $\tilde{\beta}_2$ is also large, which implies that prices drop off steeply with distance, then it must be that A is large rather than σ. However, if $\tilde{\beta}_2$ is small, then σ must be large, and A could be large or small.[31]

The residual variance in prices captured by the MSE of the auxiliary regression and the distribution of prices also help in the estimation of σ. However, because the shock term enters inside the max function in the denominator, it is the smallest shocks that matter for identification. As the log-normal distribution is bounded below by zero, this parameter is not estimated very precisely and this is reflected by the standard errors. Finally, $\tilde{\beta}_0$ reflects the scale in the auxiliary regression and therefore informs all parameters in the model.

I discuss the intuition regarding the identification of structural parameters more formally using the sensivity measures of Andrews, Gentzkow, and Shapiro (2017) and Honoré, Jørgensen, and de Paula (2020) in Online Appendix F.

To carry out the estimation, I set up the data in the following manner. First, because retail prices are only available at the level of an Indian administrative district, I assign the same retail price to all markets in a given district–time period. Second, data on retail prices are available only between 2005 and 2011, barring 2008;[32] therefore I focus on the data in these years for estimation. Third, to reduce the computational burden, I use the median prices at the crop-market-season level for estimation.[33] There is little variation in retail prices of a district or farmer prices at a market in a season (see Table I) and thus there is no consequential loss of information. However, it helps me create a balanced panel as retail prices in certain months are erroneously reported or are missing. Fourth, I exclude the states for a crop where it has never been produced. To infer this, I use the information in the crop calendar and production statistics reported by the Ministry of Agriculture of India in its annual publication, Agriculture

31. I thank an anonymous referee for helping me refine this intuition about identification.

32. 2008 was a drought year. Therefore, I am not worried about sample selection. If anything, the data would have been outliers.

33. I use three crop seasons: fall, spring, and summer.

TABLE IV
STRUCTURAL ESTIMATION RESULTS

Parameter	Point estimate	Cluster robust SE
δ	0.73	0.0025
σ	0.00039	0.0048
a	0.0016	0.0007
J-statistic	30.00	

Note. Standard errors are clustered at the state-time level.

Statistics at a Glance, for the years in my sample. I provide the details in Online Appendix J.3. This leaves me with data on eight crops in 2,978 markets for 15 time periods.

Table IV reports the estimated parameters with robust standard errors clustered at the state-time level. The bargaining ability of the farmer, δ, is estimated to be 0.73. The estimated parameters of the trade costs correspond to a deterministic 16% transport cost over a distance of 100 km. In Online Appendix H.1, I also consider other functional forms for trade costs such as a power function, a quadratic, and the exponential function. In general, the data admit any functional form for trade costs that is concave in distance.

How should we interpret $\delta = 0.73$? The bargaining power of the farmer at any location is a result of two aspects. The bargaining weight, δ, and the outside option (the Nash threat points). Conditional on δ, if a farmer at any location has a better outside option then they also have more bargaining power. Conditional on the outside option then, the bargaining weight δ represents how the surplus is split between the farmer and the trader. Therefore, my preferred interpretation is that if the outside options of both the farmer and the trader were hypothetically symmetric, the trader gets about $30\% \simeq (1 - \delta)$ of the overall surplus. This is high given that the farmer alone bears all the costs of production and transportation to the market site even if we were to account for the fact that some of the trader's share would be costs of running their business. This estimate is in line with what the literature has found using randomized experiments in India. Mitra et al. (2018), for example, estimate a 40% margin for potato intermediaries in West Bengal.

2. *Goodness of Fit.* To assess how well the model fits the data in the sample, I regress log of actual prices to log of prices

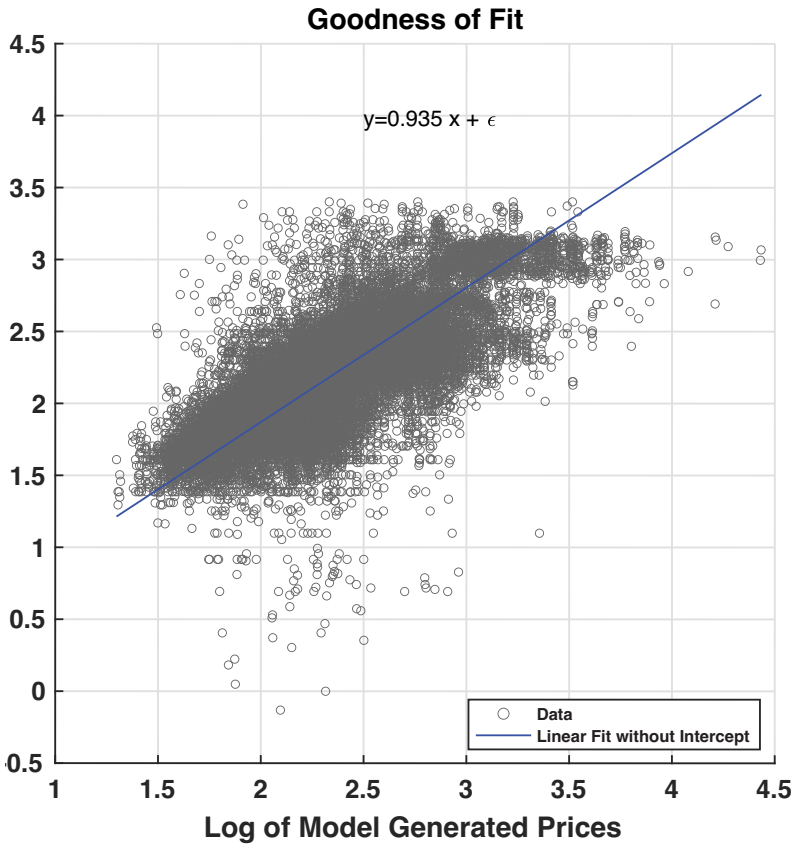

FIGURE II

Linear Fit: Data versus Model

The standard error of the slope is 0.0005.

generated from the model. A linear regression without an intercept term has a coefficient of 0.935 with an R-squared of 0.54. The fit is shown in Figure II. Figure III shows a density plot of model-generated prices and actual prices, and Table V presents different moments of the price distribution. We can notice that the model does a good job of capturing the distribution of prices. In Figure III, the humps in the density of actual data are because of different crop specific means. This is not exactly replicated in the model-generated data because I do not have any crop-specific parameters in the model.

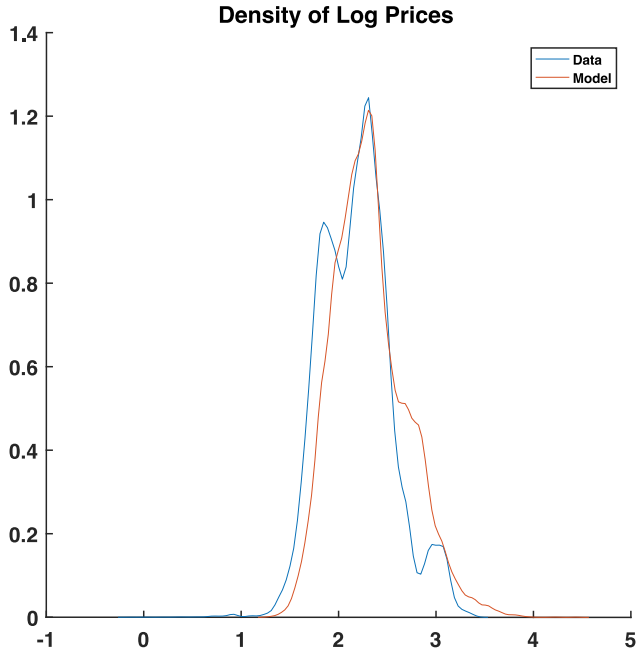

FIGURE III

Empirical Density of Prices: Data versus Model

TABLE V

GOODNESS OF FIT

Moment of farmer prices	Data	Model
Price distribution		
Mean	2.18	2.31
Variance	0.13	0.14
25th percentile	1.90	2.04
Median	2.19	2.27
75th percentile	2.39	2.54
90th percentile	2.62	2.83
Auxiliary regression model		
β_0	0.35	0.01
Max P(β_1)	0.60	0.20
Distance (β_2)	– 0.01	– 0.01
Retail price (β_3)	0.24	0.79
Root mean sq error	0.16	0.03

Finally, remember that I did not use the border regressions (4) to estimate model parameters. I can, however, replicate the border regression on model-simulated data. This yields a coefficient of 0.027 as compared with 0.035 in the actual data. Thus, I take it to be a success of the model that the model can match the distribution of prices well even without incorporating crop-specific parameters and the nontargeted border regression.

The model has a few strong assumptions. An important one being a constant Nash-bargaining parameter, δ, across crops and markets. This is due to two reasons. First, it will be computationally challenging to estimate over 2,500 parameters. Second, ideally I would need some data at the market level that would provide information to identify a local bargaining parameter. However, considering the above results, it appears that the loss from this assumption is perhaps not large. Moreover, the fact that the model can also replicate the border regression gives further credibility to the spatial competition story.

VI.B. Calibrating the Production Function and Demand Elasticities

To calibrate $\gamma + \nu$, the share of land and labor, I use the first-order conditions from the farmers' profit-maximization problem. Because of fixed factors, I need data on input costs and farm profits, which I obtain from the Situation Assessment Survey of Agricultural Households in India 2012–13.[34] I find that $\gamma + \nu = 0.57$. In Online Appendix H, I present results for other values of $\gamma + \nu$.

I take estimates of the price elasticity of demand of key cereals, $\eta = -1.29$, in India from Deaton (1997).

VII. Counterfactual Analysis

The model I have laid out allows me to compute changes in farmer prices, production, and revenues as a result of more competition between intermediary markets. In this section, I use the removal of the restriction on farmers selling in markets of other states as a convenient experiment to increase spatial competition between intermediary markets. The key mechanism is the following. Consider two markets on the Madhya Pradesh–Maharashtra

34. For details, see Online Appendix G.1.

border. Suppose that the farmer living close to the market in the state of Madhya Pradesh gets low prices because competition is low in his local region as the next market is quite far away. When we remove restrictions on farmers selling across state borders, these two markets start competing for the farmer's output. This increases prices in both these markets. The farmer, wherever he chooses to sell, is better off. Moreover, these two markets are the "threat points" to other markets nearby. As the prices increase in the border markets, they also increase in other markets and this ripple effect increases prices even in the interior of the states. This is the direct benefit to farmers via an increase in prices. In response to an increase in output prices, farmers also adjust their use of intermediate inputs, and their incomes improve further as a result of increased production. Finally, as a result of changes in production and changes in the market site where farmers choose to sell, retail prices may adjust and feed back into the prices farmers get.

In the model, this removal of trade restrictions on farmers is equivalent to changing the trade cost between two locations in different states from infinity to what it would be under equation (14). To study the role of the different channels mentioned in the previous paragraph, I conduct four exercises, relaxing one constraint at a time. In the first exercise, I do not allow retail prices to adjust. I keep all decisions of the farmer fixed except their threat to sell at a market outside the state (Section VII.A). In addition to allowing farmers to offer a different threat, in the second exercise, I allow them to choose a different market to trade in (Section VII.B). In a third exercise, I let farmers also adjust their intermediate-input choices to study the change in their crop output (Section VII.C). In the final exercise, I let retail prices at the district level adjust in response to changes in supply to understand medium-run implications for farmer prices and output (Section VII.D).

I also use the model to understand the implications of reductions in transport costs and examine the quantitative magnitudes of the interaction of such public investment with trade liberalization for farmers (Section VII.E).

Note that all these exercises require data on crop choices of farmers. For this, I use data from the Situation Assessment Survey of Agricultural Households 2012–13, and I match them with data on retail prices from 2011–12. These are the two closest years

for which I have detailed data on crop choice and retail prices.[35] Since regional cropping patterns in India have been stable over the past decade, this is not a major concern for interpreting my results.

VII.A. Changing Farmers' Threat Point

In this exercise, I use my model and estimated parameters to study what happens to farmer prices when we remove the restriction on farmers selling in markets of other states but keep all other decisions fixed. We can think of this as a hypothetical exercise where farmers go to the same market where they went when restrictions were in place. However, they can threaten intermediaries with going to a market in another state when bargaining with them.

The changes in farmer prices at the markets are presented in Figures IV and V. Figure IV plots the relationship between the change in prices in each market in the counterfactual scenario and the change in competition for each market, where competition is defined as in the reduced-form regressions using equation (1). The bottom of Figure IV plots the empirical distribution of the change in competition as a result of the removal of the interstate trade restriction. There is a monotonic relationship between price increase and increase in competition. The median increase in competition is 2.9, which means that half of all markets experience at least a 2.8% increase in price.

Figure V plots the estimated relationship between gain in price at a market and the distance to the nearest border. The bottom of the figure plots the empirical distribution of the location of markets with respect to state borders. We can see that the biggest gains are in markets closest to state borders and the gains decline the farther the markets are. However, due to the ripple effect, even markets in the interior of some states realize an increase in competition and therefore an increase in price.

To understand what this means for farmers living in different locations, I divide India into grid cells of 5 arc minute by 5 arc minute.[36] I use data on land use to exclude cells that are

35. The Central Statistical Organization of India should soon release data on retail prices from 2012–13, at which point I will update this analysis.

36. This corresponds to a cell having land area of approximately 10 km by 10 km. Although this is much larger than a typical farm, it is not a major concern because I consider a production function that is homogeneous of degree one, and

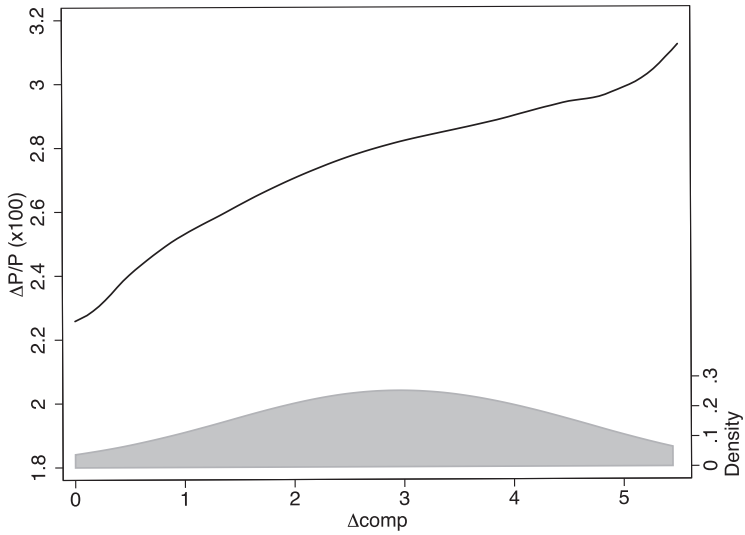

FIGURE IV

Change in Price at Each Market versus Change in Competition

The solid line is the estimated relationship between the change in price at a market and the change in competition, Δcomp, due to removal of the interstate trade restriction. Competition is measured as in the reduced-form regressions (defined in equation (1)). Estimated relationships using local linear regressions of bandwidth 1. Domain is 1st to 99th Percentile. Bottom plots the empirical distribution of the x-axis variable.

uncultivated like deserts, large water bodies, mines, and marshes. The remaining cells are hypothetical farms in India for which I compute changes in prices and production as a result of increased spatial competition in the remainder of Section VII. To determine the price the farm gets, I also need to know what crops this farm grows. I use data from the Situation Assessment Survey of Agricultural Households 2012–13 to estimate the district-level land shares for each crop in each crop season, that is, the crop choice of the district. I then assign the crop choice of the district to each cell that lies in a majority in that district.[37] I compute the price received by a farm as the Laspeyres price index. I use yield estimates from the Situation Assessment Survey of Agricultural Households

cropping patterns in India are similar within 10 km distances. Limitations of computing power do not allow for consideration of finer grid cells.

37. The quantitative results are robust to assuming that all farmers grow just the main crop of their district.

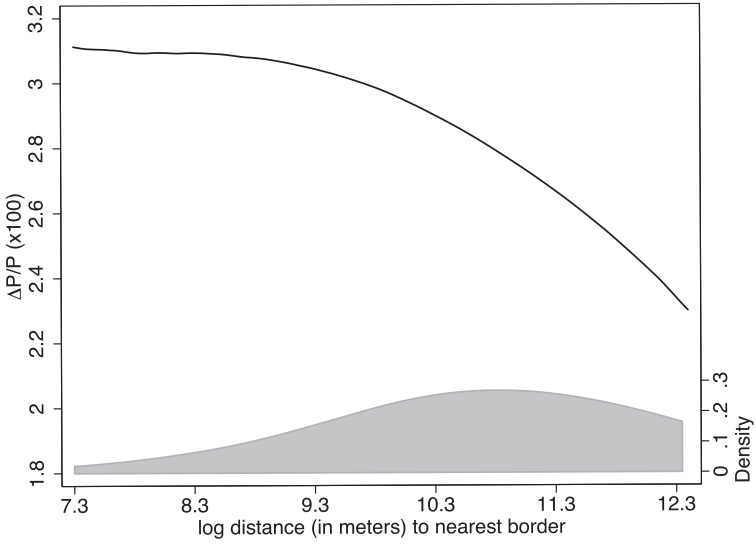

FIGURE V

Change in Price at Each Market versus Distance to Nearest Border

The solid line is the estimated relationship between the change in price at a market and the distance from the market to the nearest state border. Estimated relationships use local linear regressions of bandwidth 1. Domain is 1st to 99th percentile. Bottom plots the empirical distribution of the x-axis variable.

to estimate the quantities produced on each farm. The need for data on quantities is to ascertain the crop choice of a farm in a district and then compute the price index. For the counterfactual estimates themselves, which are computed in changes, these data are not needed.

Conditional on the crop that each farm is growing, they optimally choose a market in which to sell their output. This is simply the market where their revenues are maximized net of trade costs. In this counterfactual, this market choice of the farmer is fixed but the threat point now includes the possibility of being able to sell in any market in the country.

The results for the fall season are presented in Figure VI; Figure VII presents the results for the spring season. The average increase in farmer prices is 1.08% and 1.01% in the fall and spring seasons, respectively. The average increase in prices for the top 25% of farmers with the largest gains is 3.26% in the fall season and 3.07% in the spring season. These increases in farmer prices

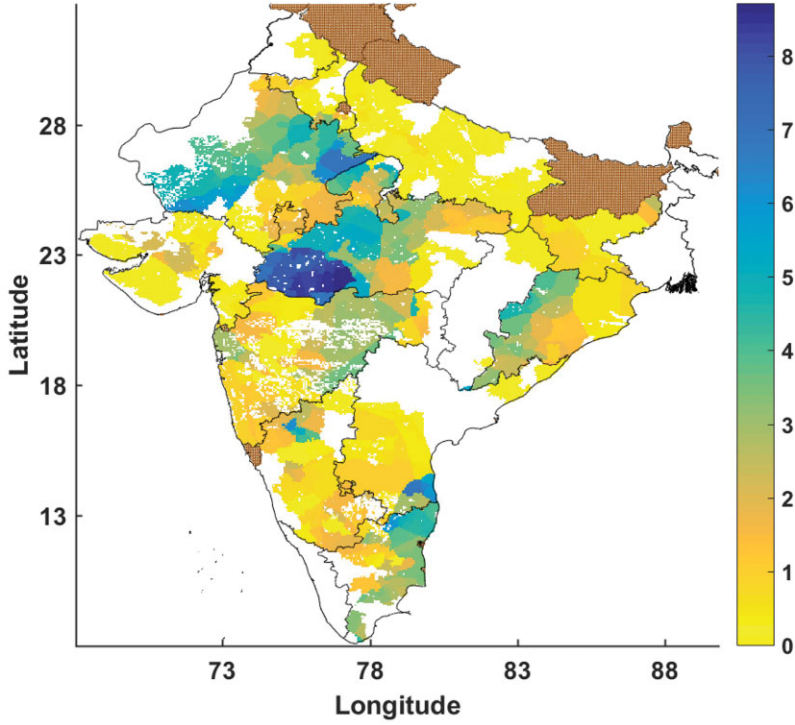

FIGURE VI

% Increase in Prices in the Fall Holding Market Choice of Farmers Fixed

Hashed brown color (color version available online) represents no data, and white represents zero gains.

are purely due to an increase in spatial competition because I do not allow farmers to change any other decision.

VII.B. Allow Farmers to Sell at a Different Market

In the second exercise, in addition to providing a greater threat to intermediaries while bargaining, I also allow farmers to choose a different market to trade in. Thus, in the counterfactual their new market choice could be another market in the same state or a neighboring state, based on where they receive the highest revenues net of trade costs. As we will see, the largest increases in farmer prices will come from changing market choice.

Figures VIII and IX present the changes in prices that farmers get as a result of increased competition because farmers can

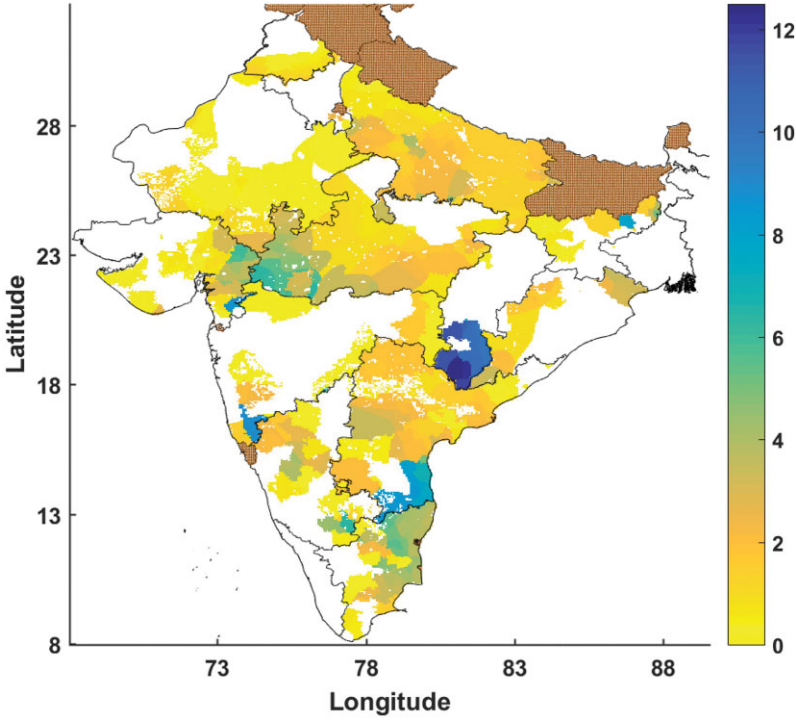

FIGURE VII

% Increase in Prices in the Spring Holding Market Choice of Farmers Fixed

Hashed brown color (color version available online) represents no data, and white represents zero gains.

sell in markets of other states. We can see that farmers are significantly better off in many regions of India. The price increases are generally larger near state borders and lower in the interior of the states. The average increase in prices is 12.6% in the fall and 10.7% in the spring. The distribution of price increases, however, is skewed. The top 50% of the farmers who experience an increase in prices get 23.37% and 20.04% higher prices on average in the fall and the spring. Consistent with Lemma 1, no farmer loses.

In the fall season, we notice bigger gains in central India (in particular, in the state of Madhya Pradesh). To explore the mechanism further, let us zoom into the Madhya Pradesh and

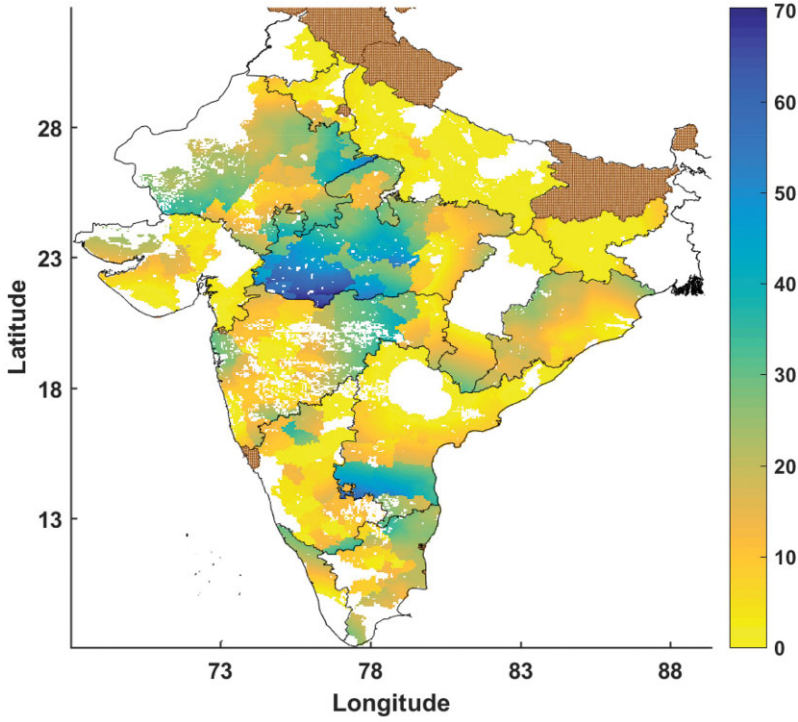

FIGURE VIII

% Increase in Prices Allowing for Optimal Market Choice: Fall Season

Hashed brown color represents no data, and white represents zero gains.

Maharashtra border.[38] This region mainly grows soybean in the fall. Figures X and XI plot the log of soybean prices that farmers get in this region before and after the policy change, respectively. We can see that price levels before the policy change are higher in Maharashtra than in Madhya Pradesh. This is so because near the state border, the density of markets is higher in Maharashtra.

After the policy change, markets on the border compete and the price in them increases. Through a ripple effect of one market affecting the other, prices increase even in the interior of the states. As can be seen in Figure XI, prices equalize on both sides of the state border. Of course, because prices were lower in Madhya

38. Refer to Online Appendix A for state names.

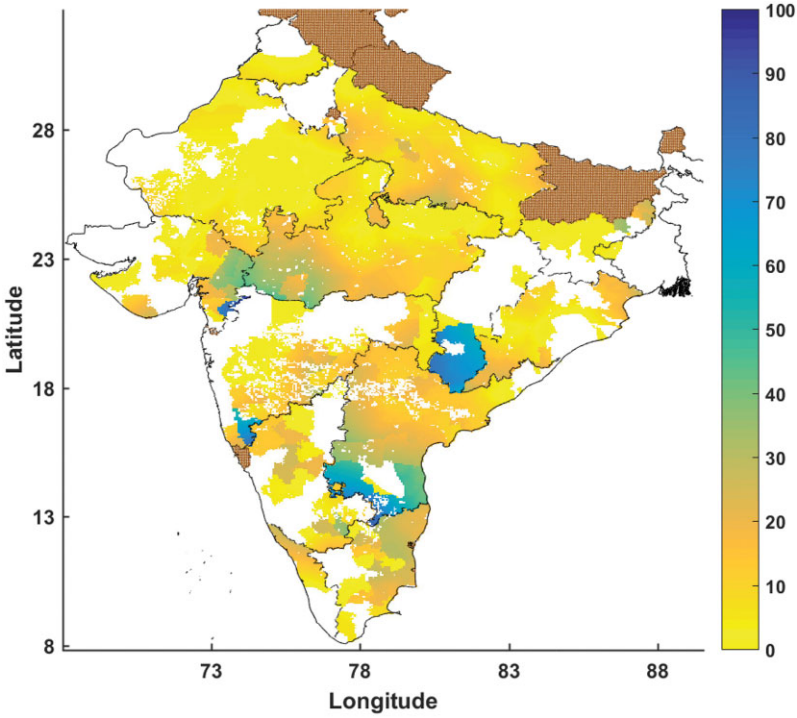

FIGURE IX

% Increases in Prices Allowing for Optimal Market Choice: Spring Season

Hashed brown color represents no data, and white represents zero gains.

Pradesh to begin with, the percentage increase there is higher (see Figure XII).

Prices increase by nearly 60% in Madhya Pradesh near its border with Maharashtra for the following reason. Farmers in Madhya Pradesh close to the border are generally far away from markets in their own state. Therefore, with border restrictions, they pay a substantial transport costs to trade in these markets. When states open up to trade, these farmers get access to markets in Maharashtra, which are much closer. This saves farmers' transport costs, leading to even larger gains.

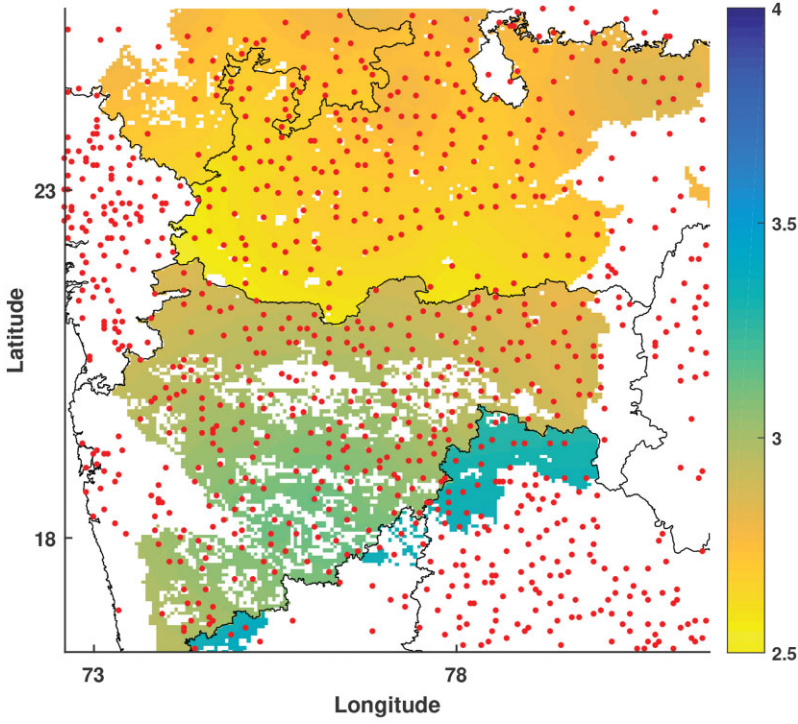

FIGURE X

Log of Soybean Prices (Rs/kilo) before Policy Change

The red dots are primary grain markets.

VII.C. *Letting Farmers Reoptimize the Use of Intermediate Inputs*

The Economic Survey of India 2015–16 documents a huge variation in the use of intermediate inputs. Farmers in more productive regions are usually more input intensive. I highlight a possible reason behind this pattern in this exercise. I allow farmers to change their use of intermediate inputs in response to the change in prices we observe in the counterfactual exercises of the previous section. From the model, we can show that for farm f, the new output (y'_f) to the old output (y_f) ratio is a function of the

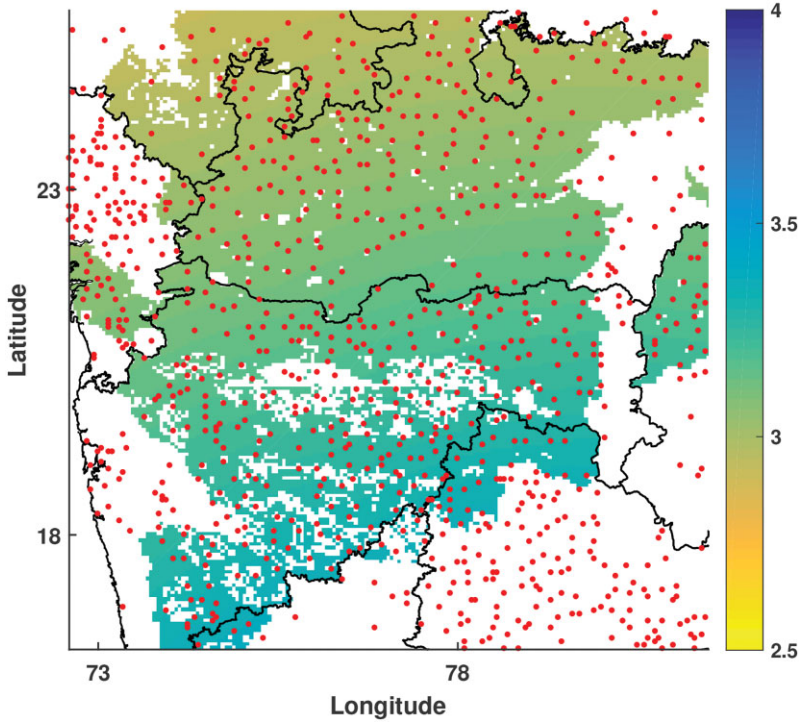

FIGURE XI

Log of Soybean Prices (Rs/kilo) after Policy Change

The red dots are primary grain markets.

ratio of the new to old prices. In particular[39]

$$\frac{y'_f}{y_f} = \left(\frac{p^{f\prime}}{p^f}\right)^{\frac{1-(\gamma+\nu)}{\gamma+\nu}},$$

where γ and ν are the share of land and labor in production, and primes represent the new output and prices. Since $\gamma + \nu < 1$, the percentage increase in production is smaller than percentage increases in prices. The results presented in Figures XIII and XIV use the same crop choices as before. To measure quantity produced at each farm, I com-

39. For a formal proof, see Online Appendix G.

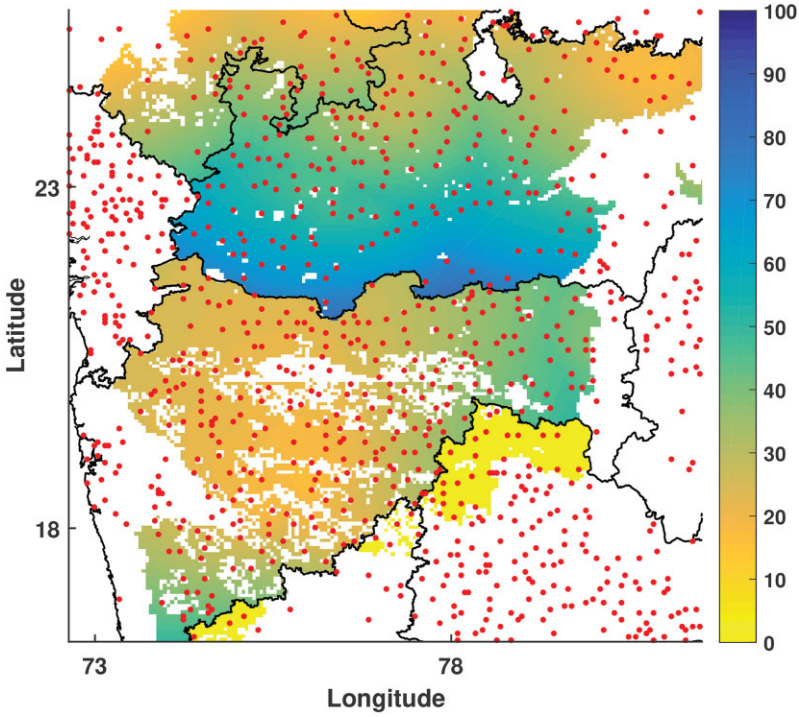

FIGURE XII

% Change in Soybean Prices in Maharashtra and Madhya Pradesh

The red dots are primary grain markets.

pute the Laspeyres quantity index. The average increase in production is 9.1% and 7.75% in the fall and the spring, respectively. The average increase in production for the top 50% of the farmers is 16.9% and 14.46% in the fall and the spring, respectively.

Farmers in less competitive regions use fewer intermediate inputs as a result of low output prices. Therefore, the benefit to farmers from the increase in competition comes from two sources—an increase in prices and an increase in quantities. This leads to an increase in the total revenue of farmers. The aggregate increase in the value of production is 17.3% in the fall season and 20.9% in the spring season.

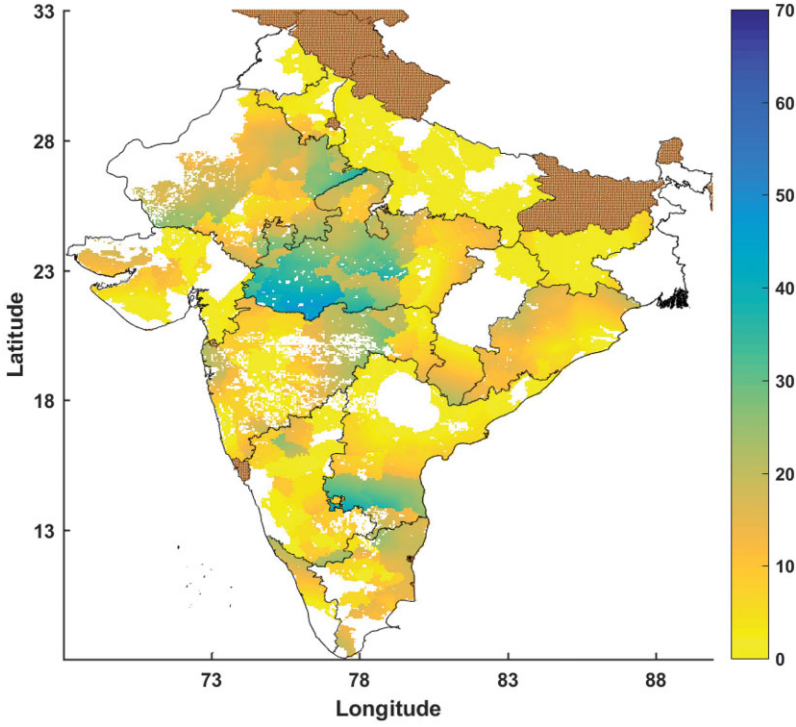

FIGURE XIII

% Increase in Production in the Fall Season

Hashed brown color represents no data and white represents zero gains.

VII.D. Incorporating a Demand Side Response

The gains described above could be overestimates because an increase in production could depress retail prices, which would feed back into farmer prices. To understand this channel better, I use estimates of demand elasticities from Deaton (1997) and an iterative algorithm that solves for the fixed point in farmer and retail prices to find the new equilibrium after border restrictions to trade are removed.[40]

Figures XV and XVI present the changes in prices incorporating adjustment of retail prices for the fall and the spring,

40. See Online Appendix I for details.

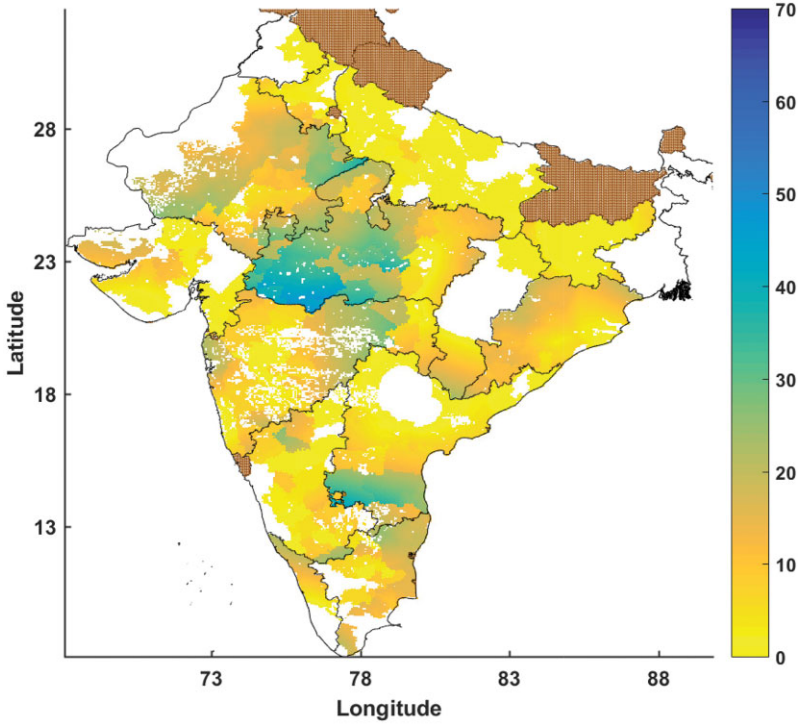

FIGURE XIV

% Increase in Production in the Spring Season

Hashed brown color represents no data and white represents zero gains.

respectively.[41] Although there are regions in the interior of some states where farmers lose, most farmers gain. The average increase in farmer prices is 9.62% in the fall season and 9.56% in the spring season. The average increase in prices for the farmers with above-median changes is about 20%. For the farmers who lose, the average decline in prices is about 10%.

The average price increases here are only marginally lower than in the exercise when I kept retail prices fixed despite a fall in prices of some farmers. The main reason is the following. When I remove the restriction on farmers to trade across state borders, supply, on average, increases in regions with high initial retail

41. Compare to Figures VIII and IX, which present changes in farmer prices when we do not allow retail prices to adjust.

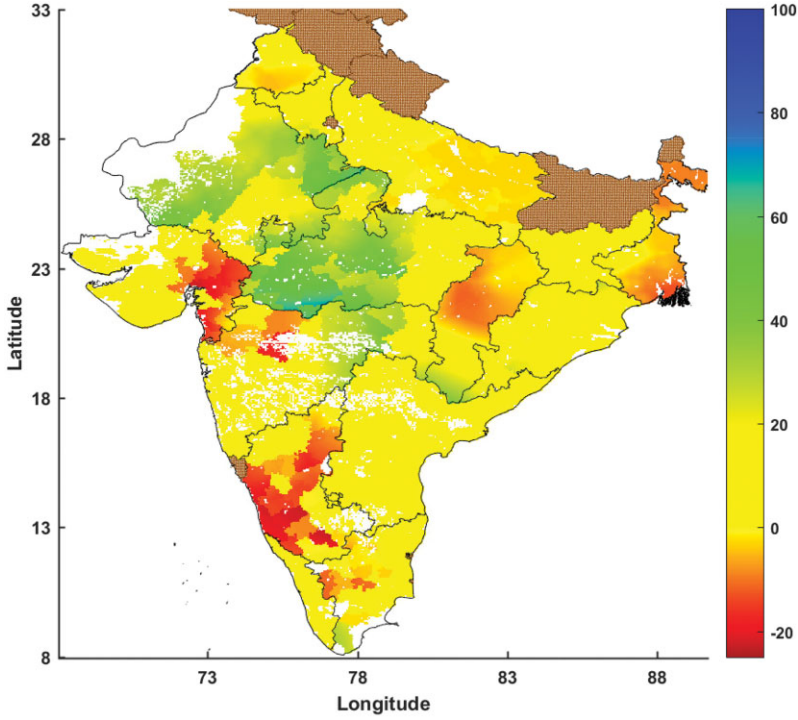

FIGURE XV

% Increase in Prices in the Fall Season Incorporating a Demand Side Response

Hashed brown color represents no data. Please see the online version for precise color scale.

prices. The supply increases because these regions attract more farmers, who in turn, produce even more as they get paid more. This adjusts the retail prices downward, and farmers from such regions lose on average. Since supply reduces in regions with low initial retail price, as farmers sell in other regions, there is an upward adjustment of retail prices on average. In equilibrium, the net effect on farmers from these regions is ambiguous. Earlier, when retail prices were held fixed, in response to removal of border restrictions these farmers incurred transport costs to get access to higher prices (Section VII.B). Now these farmers can get higher prices in their local neighborhood. These prices are not as high as in the counterfactual before, but the farmers save their transport

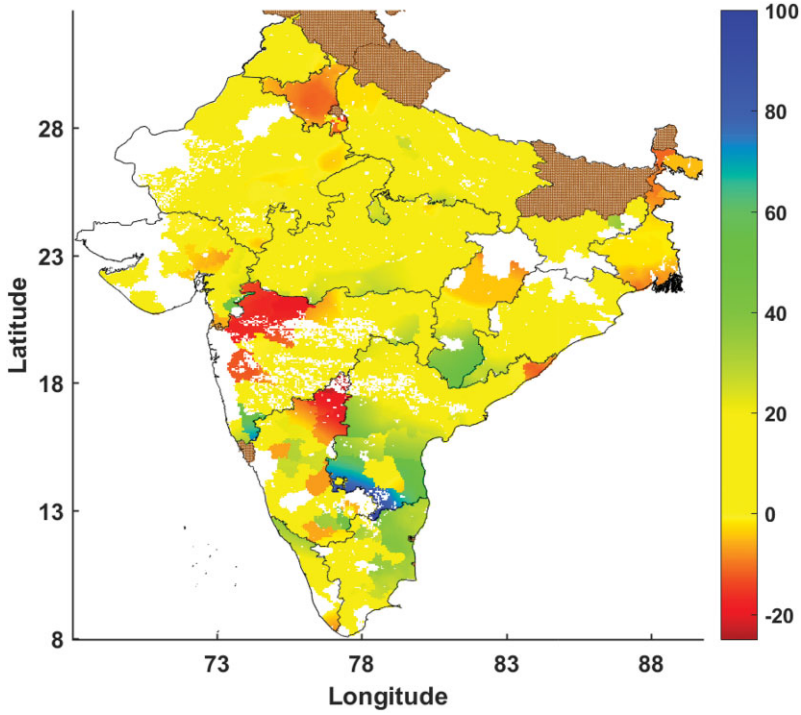

FIGURE XVI

% Increase in Prices in the Spring Season Incorporating a Demand Side Response

Hashed brown color represents no data. Please see the online version for precise color scale.

costs. Hence, in principle, some farmers can gain more as a result of the adjustment of retail prices.

The results from the exercises above are summarized in Table VI. I have shown that increased competition due to the removal of trade restrictions substantially increases the prices that farmers receive. The average farmer gets about a 10% higher price for his output. The gains are skewed as the average increase in price for the top 50% of farmers is about 19%. Approximately 6% of the increase is purely due to competition, while a majority of it comes because farmers also reoptimize their market choice and save on transport costs. Increase in price is only part of the gain that farmers get because this is reinforced by an increase in production as farmers adjust their use of intermediate inputs. As a result,

TABLE VI

SUMMARY OF COUNTERFACTUAL EXERCISES

Change in farmer prices (%)	Median		Mean		Mean for the top 50%		Mean for the top 25%	
	Fall	Spring	Fall	Spring	Fall	Spring	Fall	Spring
1: Change the treat point	0.38	0.41	1.08	1.01	2.11	1.98	3.26	3.07
2: 1+market choice	8.35	5.82	12.60	10.72	23.37	20.04	32.67	29.69
3: 2+adjust retail price	5.98	6.21	9.62	9.56	20.32	19.49	31.70	28.74

the total value of production increases by about 19.90%. Finally, I allay concerns that an increase in output might reduce retail prices so much that farmers in most regions end up losing.

VII.E. Effect of a Reduction in Transport Costs

The exercises that I have presented so far reflect the direct gains from competition via increased prices for farmers. Spatial competition can also interact with other development policies in interesting ways, and I can use my model to shed some light on this aspect. Poor roads and lack of access to good vehicles increase transportation costs in India, and they are especially high for farmers (Kapur and Krishnamurthy 2014). However, since 2007, the central government has invested around $40 billion in the construction of rural roads (Chatterjee and Kapur 2017). Between 2001 and 2015, approximately 185,000 habitations have been connected by all-weather roads. The goal in this section is to show that farmers can realize substantially greater benefits of such public investments in the presence of greater competition among intermediaries.

I consider reducing A by 40%, and for illustrative purposes, I present results only for the fall season. Figure XVII presents the increase in farmer prices due to a reduction in transport costs in the fall season in the presence of border restrictions. Figure XVIII presents the additional increase in farmer prices due to more spatial competition in the absence of border restrictions to trade. I computed this by calculating the increase in farmer prices due to simultaneously reducing the transport costs and removing the border restrictions, and then subtracting the increase in prices just due to the reduction in transport costs (computed in Figure XVII) and the increase just because of the elimination of border restrictions to trade (computed in Figure VIII). Farmer prices increase by an additional 8% on average, because of increased spatial competition.

We can draw two lessons. First, a reduction in transport costs, even in the presence of border restrictions, leads to increases in farmer prices in the interior of states as farmers can travel farther, and this changes their threat point in the bargaining problem. Second, the additional gains from the increase in spatial competition occur in those regions where transport cost reduction was not effective in improving farmer prices, for example, in the states

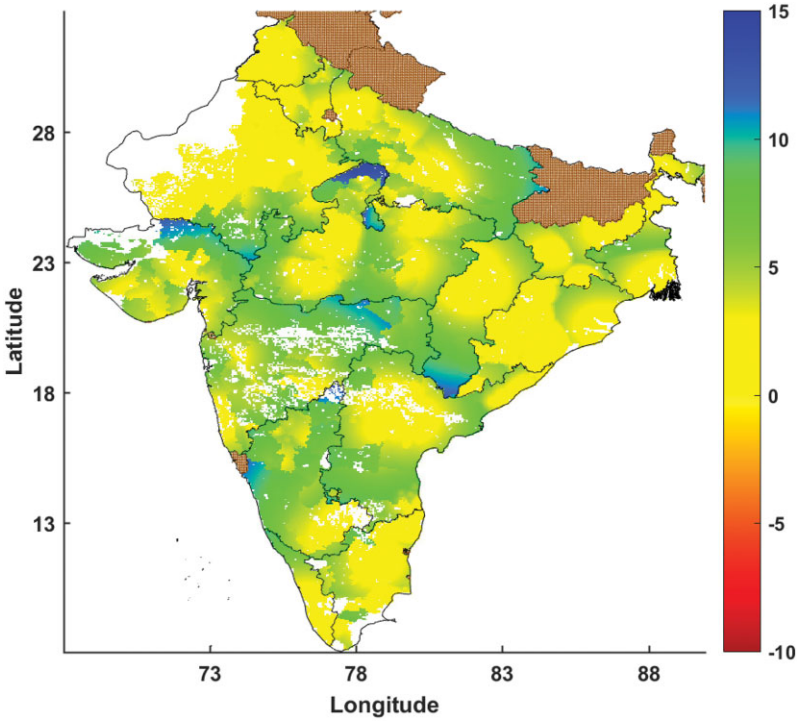

FIGURE XVII

% Increase in Prices due to Reduction in Trade Costs with Border Restrictions

Hashed brown color represents no data. Please see the online version for precise color scale. Estimates are for the fall season.

of Odisha, Madhya Pradesh, and Rajasthan.[42] Therefore, transport infrastructure polices can be thought of as complements to policies that increase competition.

VIII. CONCLUDING REMARKS

The median annual farmer income in India is US$ 365 (Ministry of Finance, Government of India 2016). In this article, using unique data on the location of intermediary markets and farmer prices, I have shown that spatial competition between intermediaries is an important determinant of the prices that farmers in

42. For state names, see Online Appendix A.

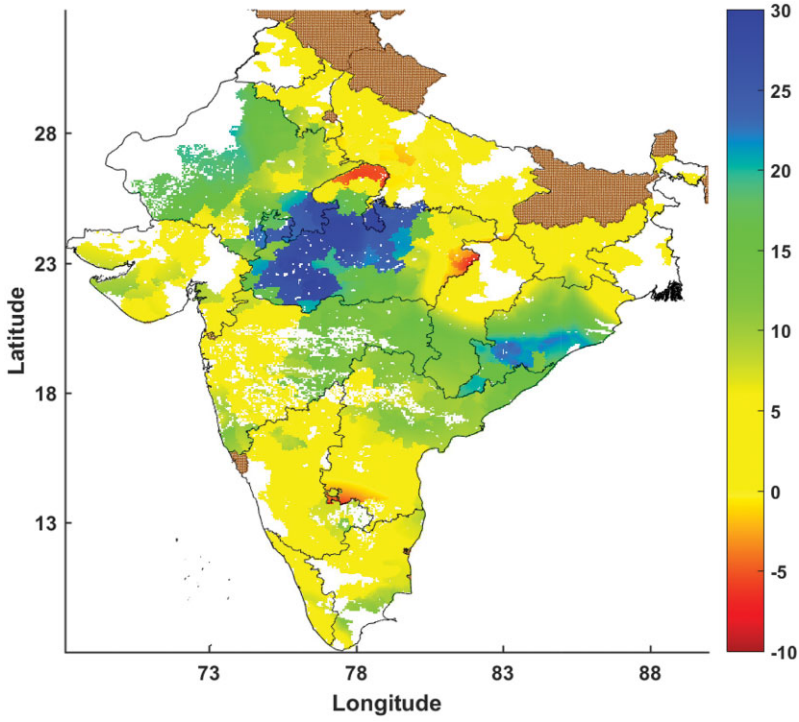

FIGURE XVIII

Additional Changes in Prices (%) Because of a Reduction in Trade Costs and Elimination of Border Restrictions

Hashed brown color represents no data. Please see the online version for precise color scale. Estimates are for the fall season. To compute the changes, I first compute changes in prices due to a reduction in trade costs and elimination of border restrictions. From this I subtract the gains in prices just due to reduction in trade costs (Figure XVII) and just due to elimination of border restrictions to trade (Figure VIII).

India get for what they produce. High transport costs and policies that limit the ability of farmers to arbitrage between different intermediaries cause the market power of intermediaries to vary in space. Farmers who live in regions where there is more competition between intermediaries receive higher prices for their output. A one standard deviation increase in competition increases farmer prices by 6.4%.

I also show that increasing competition in one region spreads through the rural economy via a ripple effect. In particular, I

consider the effect of reforming the laws of Indian states that prohibit farmers from selling in markets of other states. I show that such a policy increases incomes of farmers who live close to state borders and those living in the interior. I also show that increased competition further increases farmer incomes because of the increased output of farmers as they optimize the use of intermediate inputs. I find that the average increase in prices and output for the farmers with above-median gains is about 21% and 15%, respectively. Furthermore, the value of national crop output increases by about 18%. Moreover, the results indicate that isolated studies in agricultural markets can indeed find varying estimates of market power of intermediaries because they are partly driven by spatial competition.

It is worth noting that in this model, improving market access increases spatial competition concomitantly. Market access is improved either by reducing trade costs or removing border restrictions to trade. In either case, the value of the outside option in equation (11) increases, increasing spatial competition. As such, it is hard to imagine a scenario where the degree of spatial competition can be increased without improving market access. However, the model allows us to evaluate the hypothetical scenario where we fix the market choice of farmers but allow them to use larger threats while bargaining. In Section VII.A, I show that this improves prices in at least 50% of the markets by at least 3%. However, the larger gains occur because farmers can access those markets where prices are higher due to spatial competition.

Finally, I document that there are large complementarities between market integration and spatial competition. Adding to the large literature on how reductions in trade costs affects market integration and gains from trade (summarized in Donaldson 2015), I show that welfare benefits of market integration and trade cost reduction are substantially more in the presence of greater competition.

The results in the article must be read with the following caveats. First, in the policy counterfactual exercises, I reduce the trade cost between state borders to just as much as predicted by the trade cost function. This ignores "border effects"—the additional trade cost of crossing borders even if there were no regulatory barriers. Although such border effects are mostly present between countries, they could be present between states in India and cannot be completely ruled out. The placebo border regressions on retail prices imply that such interstate

border effects are likely small if present. Thus, the magnitudes coming out of the structural exercise would be a small overestimate of the true effects to the extent that such border effects are present.

Second, I take the political and social complexities of rural India as given and keep them fixed in the counterfactual simulations. Further, the market for inputs—seeds, fertilizers, and labor—are assumed to be perfectly competitive with inelastic supply. These assumptions are fine to a degree, especially the markets for seeds, irrigation, and fertilizers as they are controlled by the government. However, very large changes can affect these factors and have bearing on the quantitative counterfactuals. Third, I have assumed that farmers directly sell in markets. In reality, this may not be the case for the very small and marginal farmers who mainly cultivate for subsistence and have limited surplus. They either sell to a larger farmer or a village aggregator, who in turn sells in the market to a licensed trader. Without further information, it is impossible to distinguish between the cultivator farmer and the seller, and estimate the net change for the cultivator farmer. If the village aggregator always gives a fixed share to the small farmer in the village, then the counterfactual changes in percentages are still valid.

Although I have focused on one institutional feature in one particular developing economy, I believe that these findings have broader importance. Similar institutions and policies exist elsewhere. Monopsony power of agricultural marketing boards or intermediaries is a common feature across developing countries (see Bates 1981). Policies that restrict trade through intermediaries exist even outside agriculture. For example, until 2004 medium-sized firms in China were required by law to export via government-approved intermediaries (Bai, Krishna, and Ma 2017). The underlying mechanism of spatial competition will apply to all such environments and future work could study its importance in other settings.

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SUPPLEMENTARY MATERIAL

An Online Appendix for this article can be found at *The Quarterly Journal of Economics* online.

Data Availability

The data underlying this article are available in the Harvard Dataverse, https://doi.org/10.7910/DVN/IWFR5R (Chatterjee 2023).

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