

University of Toronto  
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Working Paper 798

Misallocation in Indian Agriculture

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March 20, 2025

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March 2025

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## ABSTRACT

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We exploit substantial variation in land-market institutions across Indian states and detailed household-level panel data to assess the effect of land-market distortions on agricultural productivity. We develop a model of heterogeneous farms and distorted land markets, featuring (a) state-level barriers to land-market participation and (b) idiosyncratic (farm-level) distortions to farm size. We use the framework to separately identify and estimate the two sources of land-market distortions in each state using farm data on productivity, land endowment, land-market participation, and operational farm size. We find substantial differences across states in land-rental barriers with large negative effects on agricultural productivity. An efficient reallocation of land in India increases agricultural productivity by 65 percent and by more than 100 percent in some states, with more than 50% of these effects attributed to state-level rental barriers. Distortions associated with land-market participation contribute substantially to agricultural productivity differences across Indian states.

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*JEL* classification: O4, O5, O11, O14, E01, E13.

*Keywords:* Productivity, agriculture, distortions, land rentals, states, India.

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<sup>†</sup>We thank the editors, two anonymous referees, Murat Celik, Joseph Cummins, Doug Gollin, Steven Helfand, Serdar Ozkan, Xiaodong Zhu, and seminar participants at the University of Toronto, Oxford, UC Riverside, and Bristol for useful comments and suggestions. All errors are our own. Bolhuis acknowledges the support from the Ontario Trillium Foundation and thanks the Department of Economics and the Centre for the Study of African Economies at the University of Oxford for their hospitality while writing this paper. Restuccia acknowledges the support from the Canada Research Chairs program and the Bank of Canada Fellowship program. The views expressed herein are those of the authors only and do not necessarily represent the views of the Bank of Canada and the IMF, its Executive Board or IMF management. *Contact:* [mbolhuis@imf.org](mailto:mbolhuis@imf.org), [s.rachapalli@sauder.ubc.ca](mailto:s.rachapalli@sauder.ubc.ca), and [diego.restuccia@utoronto.ca](mailto:diego.restuccia@utoronto.ca).

# 1 Introduction

Low productivity in agriculture is a key contributor to the large income differences between rich and poor countries ([Gollin et al., 2002](#); [Restuccia et al., 2008](#)). While the evidence suggests that poor countries are characterized by lower allocative efficiency across production units that dampen aggregate productivity ([Adamopoulos and Restuccia, 2014](#)), the sources of these inefficiencies are less well understood. In this paper, we explore one potential source of low agricultural productivity in developing countries, the misallocation of factors of production associated with land-market institutions, and examine differences in land-market institutions across states in India. By focusing on differences in institutions within a country, we address a common challenge in cross-country studies where land institutions may be related with other factors that affect agricultural productivity. We consider the substantial variation in land institutions across states in India that have their origins in the nature and timing of the colonial conquest across regions. We emphasize state-level differences in barriers to land rental-market participation and the substantial role they play in depressing agricultural productivity across Indian states.

India provides a unique setting to study land markets and agricultural productivity for three reasons. First, agricultural labor productivity in India remains very low despite strong advances in other countries. For instance, real value added per worker in 2010 Indian agriculture was only 5 percent of that in the United States, whereas in non-agriculture this ratio was 32 percent; and the share of employment in agriculture in India remains very high, 58 percent in 2010, indicative of a low agricultural productivity level ([Timmer et al., 2015](#)). Second, Indian states exhibit substantial variation in both land institutions and agricultural outcomes. The variation in GDP per worker in agriculture across states in 2011-12 is a factor of 13.5-fold and the share of employment varies between 5 and 75 percent ([MOSPI, 2011](#); [Census of India, 2011](#)). These are enormous variations across states that resemble the patterns observed across countries but that occur within a common national institutional

framework. The market for buying and selling of land is virtually non-existent in all states in India as most agricultural land is inherited ([Foster and Rosenzweig, 2017](#)). At the same time, states in India exhibit different degrees of land rental-market activity that allow us to study the effects of rental barriers separately from farm-level distortions associated with other aspects of land institutions in Indian states. Third, we use detailed household-level data, collected under the same survey design across all states, that distinguishes between cultivated land, owned land, and leased land. This feature of the data allows us to separately identify state-level rental barriers from idiosyncratic (farm-level) distortions faced by farmers participating in the land-rental market.

We document large differences in land institutions across states in India resulting from both historical variation in land revenue systems under the British rule and state-level variation in post-independence land reforms ([Besley and Burgess, 2000](#); [Banerjee and Iyer, 2005](#); [NITI Aayog, Govt. of India, 2016](#)). In an attempt to protect tenants from exploitation by landowners, states imposed restrictions on land-leasing, but to different degrees. Some states, such as Kerala, explicitly prohibit the leasing of land. Others, such as West Bengal, only allow sharecropping. Land reforms also impacted landowners' willingness to rent out land either formally or informally for fear of losing their land to tenants. As a result, land rental activity differs markedly across states.

To quantify the importance of land-market distortions in Indian states for agricultural productivity, we use household-level data from two waves of the Indian Human Development Survey (IHDS), wave I 2004-2005 ([Desai et al., 2005](#)) and wave II 2011-2012 ([Desai et al., 2012](#)). The IHDS contains not only detailed information on farm-specific agricultural output and inputs, but also information on the amount of land that a household owns and leases to or from other land-market participants. We exploit the panel structure of the data to construct a robust measure of farm-level total factor productivity (TFP) as the household fixed effect of a panel regression, thus removing any systematic and idiosyncratic shocks to productivity over time, and then adjusting for state-level factors. Using the estimates of

farm productivity, we characterize misallocation in each state and provide evidence on the strong link between land rental-market activity and misallocation across states in India.

To examine how land-market distortions affect the allocation of land and agricultural productivity across states, we embed the production framework into an equilibrium model of heterogeneous farms and distorted land markets. We model two sources of land-market distortions that create resource misallocation. First, we introduce a novel type of distortion where farmers face state-wide barriers to engaging in rental-market transactions, which manifest themselves as a difference between a farmer’s cost and return to leasing land. This feature is motivated by two important observations: (a) land institutions vary across states and these institutions imply disparate restrictions on renters and rentees and (b) the extent of land rental market participation of farmers varies across states. We show that the wedge between the land price to rent in and rent out results in some farmers choosing not to participate in the rental market. Second, farmers face idiosyncratic (farm-level) distortions to implicit rental prices, a more standard component of misallocation. We show that these two sources of distortions can be separately identified and estimated in our framework using the household-level data on farm productivity, land endowment, rental-market participation, and operational scale of farms. We show that among rental-market participants, measured idiosyncratic (farm-level) distortions are well approximated by a systematic component with respect to farm productivity, summarized by an elasticity parameter; and a random component summarized by a dispersion parameter of a log normal distribution ([Restuccia, 2019](#)). We exploit these empirical features to parameterize idiosyncratic land distortions in our quantitative analysis.

We apply the structural framework by estimating the parameters of state-level and farm-specific distortions using the first-order conditions from the farm’s profit maximization problem. We identify distortion parameters using three sources of variation in the data: (a) the share of farmers not participating in land-rental markets, (b) the covariance between the marginal product of land and productivity across farmers, and (c) the overall variance of the

marginal product of land across farmers. We confirm a strong link across states between the estimated rental barriers and the share of farms not participating in land-rental markets, the elasticity of farm distortions with respect to productivity and the covariance between the marginal product of land and productivity, and the variance of farm-level distortions and the variance of marginal product of land across farms.

We use the estimated model to perform counterfactual experiments in order to quantify the effects of land-market distortions on agricultural productivity across Indian states, and in particular to assess the role of state-level rental barriers separately from the more standard idiosyncratic (farm-level) distortions. We find that land-market distortions have substantial negative effects on agricultural productivity with important differences across states: an efficient reallocation of land in India would increase agricultural productivity by 65 percent and by more than 100 percent in some states. More importantly, more than 50% of these effects are attributed to state-level rental barriers. For instance, in Tamil Nadu where rental barriers imply an effective tax rate on rental income of more than 95%, eliminating rental barriers contribute to an increase in agricultural productivity of 139 percent. In Karnataka and Maharashtra, the increase in agricultural productivity associated with rental barriers is 46 and 45 percent, respectively. Even in Punjab, the state with the lowest efficiency gains at 25 percent, rental barriers contribute to 14 percentage points of these gains. Land market distortions associated with barriers to land-market participation contribute substantially to agricultural productivity differences across states.

Our work relates to the broad literature on resource misallocation ([Restuccia and Rogerson, 2008](#); [Hsieh and Klenow, 2009](#)) and within this literature articles emphasizing misallocation in agriculture ([Adamopoulos and Restuccia, 2014, 2020](#); [Chen et al., 2023](#); [De Janvry et al., 2015](#); [Chen, 2017](#); [Gottlieb and Grobovšek, 2019](#); [Chari et al., 2021](#); [Le, 2020](#)). We contribute to the literature on land misallocation by exploiting a feature of our data that allows us to identify state-level barriers to rental-market participation as well as idiosyncratic (farm-level) distortions among farmers that participate in rental markets. Since our data allow

us to differentiate between endowed land and operated land, we are able to shed light on an important feature of land misallocation in agriculture: the extensive margin of farmers' rental market participation. The typical approach in the literature is to assume that all farmers have access to land markets and estimate frictions that affect the intensive margin of land use. We argue that important institutional differences across states such as restrictive tenancy laws and quality of land records can manifest as rental barriers that result in farmers not participating in land markets altogether.

We also connect with a literature studying the impact of economic institutions in India (Besley and Burgess, 2004; Aghion et al., 2008; Boehm and Oberfield, 2020) and land institutions (Besley and Burgess, 2000; Banerjee et al., 2002; Banerjee and Iyer, 2005; Besley et al., 2016). We also build on the literature using household-level data to study agricultural productivity in India such as Rosenzweig and Wolpin (1993) and Foster and Rosenzweig (1995). A key difference is that we focus on the effect of property rights institutions on agricultural productivity through misallocation. By emphasizing rental markets, we relate to a large literature studying institutions and land markets (Deininger and Feder, 2001; Holden et al., 2011; Chen et al., 2022; Beg, 2021). Our strategy of analyzing variation across states in India is inspired by the work of Lahiri and Yi (2009) who emphasized the relative economic performance of West Bengal and Maharashtra, two important states in India, using a general-equilibrium sectoral model.

The paper proceeds as follows. In the next section, we describe the institutional context of India, with reference to the determinants of land-market institutions across states. We also provide details of the data, our estimate of farm productivity, suggestive evidence of the link between land rental-market participation and misallocation, and a discussion of potential mismeasurement. Section 3 describes the model of heterogeneous farms and distorted land markets and discusses the identification and evidence of land-market distortions. In Section 4, we estimate the parameters of land-market distortions in each state and provide our main quantitative results. We conclude in Section 5.

## 2 Context

We provide a brief description of the institutional context regarding land across states in India, details of the data and variables we use in our analysis, and a characterization of the extent of land rental markets and misallocation across Indian states. The discussion of institutional context is to highlight differences across Indian states and the importance of studying them as separate markets with specific frictions. While we do not use these institutional details in our quantitative analysis, we show suggestive evidence that they contribute to land misallocation in states.

### 2.1 Land Institutions in India

Present day variation in land institutions across India is a combined result of differences in colonial land administrative systems and land reforms undertaken by state governments after independence in 1947. There were three types of land revenue systems in British India: (i) landlord-based, which assigned property rights to the landlord in charge of collecting rents; (ii) individual-based, where individual farmers had property rights and taxes were collected directly from them; and (iii) village-based, where property rights were diffused depending on who was in charge of collection.

[Banerjee and Iyer \(2005\)](#) argue that the choice of revenue system by the British across Indian regions were mostly influenced by individual administrators, precedents prior to annexation and political events unrelated to factors determining agricultural productivity. As a result, regions in India experienced different degrees of land inequality and tenant exploitation prior to independence. After independence, the 1949 Indian Constitution granted states full control over their land administration law and land-tenure issues, as a nationwide policy would not work for all states. The key elements of state land reforms were the abolition of intermediaries, regulation of the size of land holdings (land ceiling legislation), and tenancy



reforms to improve tenure security. Appendix A provides details on all types of land reforms enacted by each state (see Table A.1).

We focus our discussion on tenancy reforms enacted by the states since these institutions impose heavy restrictions on the leasing of agricultural land, which tend to prevent the reallocation of land to more efficient use. There is important variation across states in the intensity of leasing restrictions. Some states such as Kerala and Jammu & Kashmir legally prohibit leasing agricultural land, whereas Andhra Pradesh and Rajasthan allow leasing only under restrictions involving sharecropping or minimum lease periods. Appendix A (Table A.2) provides a detailed summary of all tenancy reforms implemented by Indian states between 1950 and 1980. The implementation of tenancy reforms reduced formal land rental market activity in India: the share of households reporting leasing land declined from 26% in 1970 to 12% in 2001 (World Bank, 2007). While informal and short-term tenancies continue to exist, they lack recognition leading to a lack of access to credit and other benefits that prevent farmers to cultivate land efficiently.

Restrictive tenancy laws also discourage landowners from leasing out land even in regions where leasing is legal or where informal leasing is widespread but ignored by the government. Some landowners prefer to keep their land fallow for fear of losing their land. This suggests that renters and rentees face different frictions to participating in the land rental market, which is a feature of the institutional setting that we exploit in our quantitative analysis.

The different revenue collection systems under the British also resulted in variation in the quality of land records maintained across India. The degree to which the British depended on land records to collect taxes varied based on the revenue collection system in place. Independent India inherited this variation in land records and titles, leading to vast regional differences in the quality of land property rights.

India also follows a *deeds* registration system to facilitate land transactions, which cannot guarantee the legality of a transaction (World Bank, 2007; Mishra and Suhag, 2017). The low

quality of land records and the historical registration systems imply that the registrar has no obligation or ability to check whether a transaction is valid. The right claimed in a registered deed usually has priority over unregistered ones, and subsequently registered deeds. This makes land titles in India presumptive. Moreover, the burden of verifying the validity of a seller's ownership claims is borne by the buyer, who also incurs the cost of an invalid transaction. In 2004 India ranked 123 out of 140 countries in terms of the cost of registering land transfers measured as a share of property values (e.g. high stamp duties, complex regulations, and money and time spent on duplicate and inefficient procedures) ([World Bank, 2007](#)). In contrast, under a *title* registration system the government provides and guarantees the information about past ownership, and the buyer cannot be sued for damages in case of a fraudulent transfer. While reforms have been implemented to consolidate and digitize land records (Digital India Land Records Modernization Programme), the outcomes are limited since states vary in terms of the scope of historically inadequate land records and the extent of computerized records presently ([Mishra and Suhag, 2017](#)). For instance, as of 2019 the percentage of digital Record of Rights issued by states varies from close to 100% in Andhra Pradesh, Tamil Nadu, and Tripura to close to 3% in Haryana ([Department of Land Resource, Government of India, 2020](#)).

Without well-defined land property rights, Indian farmers face frictions in accessing land rental markets as well as credit markets. The absence of clear land property rights has also contributed to land-related conflicts. There is also large variation in backlogs of land-related cases across states in India: the share of pending land-related cases that are more than 10 years old range from 45% in Gujarat (GJ) and Uttar Pradesh (UP) to 0% in Punjab (PB) and Haryana (HR).

## 2.2 Data

We use panel micro data from the India Human Development Survey (IHDS). This is a panel household-level survey that contains detailed information on agricultural and other commercial activities. The survey is representative at the state and country level in India. We use two available waves: wave I corresponding to years 2004-2005 (Desai et al., 2005) and wave II corresponding to years 2011-2012 (Desai et al., 2012). For households operating in the agricultural sector, the survey provides detailed information on farm output and all inputs into production. We focus on the household farm as our unit of analysis as opposed to a plot of land operated by the household farm (Aragón et al., 2024).

The primary variables we use in our analysis are farm output, and various farm inputs such as labor, capital (machinery, draft animals, and rented capital services), intermediates (seeds, fertilizers, pesticides), and most importantly, operated land. The survey reports three primary categories of land for each household: (a) own land cultivated by the household, (b) own land rented-out, and (c) other land rented-in for cultivation by the household. We use total cultivated land (own land plus rented in land minus rented out land) as our measure of operated land by the farm household. We construct a farm indicator of renting-out if the household reports a positive value in land rented out and another farm indicator of renting-in if households report a positive value in land rented in.<sup>1</sup>

We construct measures of real gross output, and input levels and expenditure using common prices and deflators as necessary. Appendix B.1 describes in detail the construction of real gross output and input measures from the reported household-level data. After restricting our analysis to states with an estimated population of more than 20 million, we construct a balanced panel of 8,147 households in 15 states for the analysis. Sample selection details are also described in Appendix B.1.

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<sup>1</sup>A very small fraction of farms ( $\approx 0.32\%$  of our final sample) report positive values of land rented out and rented in. We classify these households as renting in or renting out based whether they are net renters or renters.

Table 1: Average Farm Size and Land Distribution in Indian States

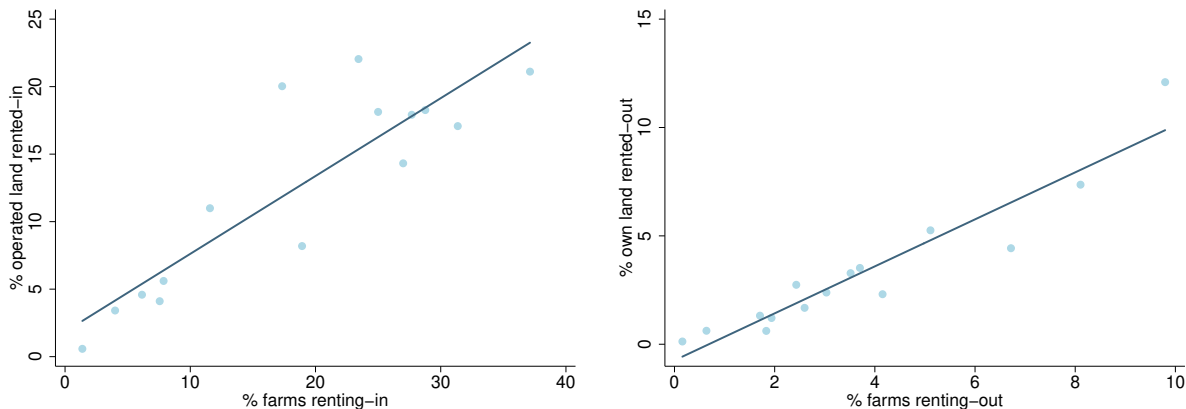
	Ag. Census (2010-11)			IHDS-II (2011-12)		
	Avg. Size	% $\leq$ 2 Ha	% $\geq$ 20 Ha	Avg. Size	% $\leq$ 2 Ha	% $\geq$ 20 Ha
India	1.15	85.0	0.12	1.45	79.4	0.20
State:						
[AP] Andhra Pradesh	1.08	86.0	0.03	2.12	59.7	0.00
[AS] Assam	1.10	85.5	0.08	1.05	89.5	0.00
[BR] Bihar	0.39	96.9	0.00	0.86	90.6	0.00
[GJ] Gujarat	2.02	66.4	0.11	2.39	64.6	0.67
[HR] Haryana	2.25	67.5	0.54	1.68	69.5	0.00
[KA] Karnataka	1.55	76.4	0.08	1.92	70.1	0.03
[KL] Kerala	0.22	98.9	0.00	0.64	93.6	0.00
[MP] Madhya Pradesh	1.78	71.4	0.11	2.58	65.7	0.68
[MH] Maharashtra	1.44	78.5	0.06	2.20	62.7	0.67
[OR] Orissa	1.03	91.8	0.02	1.01	85.3	0.00
[PB] Punjab	3.76	34.1	1.01	2.76	53.8	0.88
[RJ] Rajasthan	3.06	58.3	1.31	1.54	77.8	0.12
[TN] Tamil Nadu	0.79	91.7	0.03	1.01	91.0	0.67
[UP] Uttar Pradesh	0.75	92.4	0.01	0.93	89.0	0.00
[WB] West Bengal	0.77	95.9	0.00	0.62	95.4	0.00

**Notes:** All data refers to cultivated land by farms in hectares. Data from 2010-2011 Agricultural Census ([Agriculture Census Division, 2011](#)) and from IHDS wave II 2011-2012 ([Desai et al., 2012](#)). We focus on the largest 15 states with population size greater than 20 million.

Differences in land legislation and administration across states are at the heart of contemporaneous differences in the operational scale of farms. Table 1 reports the average farm size and other moments of the distribution of cultivated land in farms across states in India using data from the 2010-2011 Agricultural Census ([Agriculture Census Division, 2011](#)) and IHDS wave II 2011-12 ([Desai et al., 2012](#)). We emphasize two observations from Table 1. First, the survey data provide a good characterization of farm land sizes in Indian states as compared with the Census data. Second, there are substantial differences in average farm sizes across states consistent with differences in land institutions. For example, in our survey Punjab’s average farm size is more than 4-fold that in Kerala (2.76 to 0.64 ha). In Punjab,

53.8 percent of farms operate less than 2 hectares of land, whereas in Kerala 93.6 percent operate less than 2 hectares. These differences in the operational size of farms resemble the large differences in farm size observed between rich and poor countries ([Adamopoulos and Restuccia, 2014](#)).

Figure 1: Land Rental Market Activity

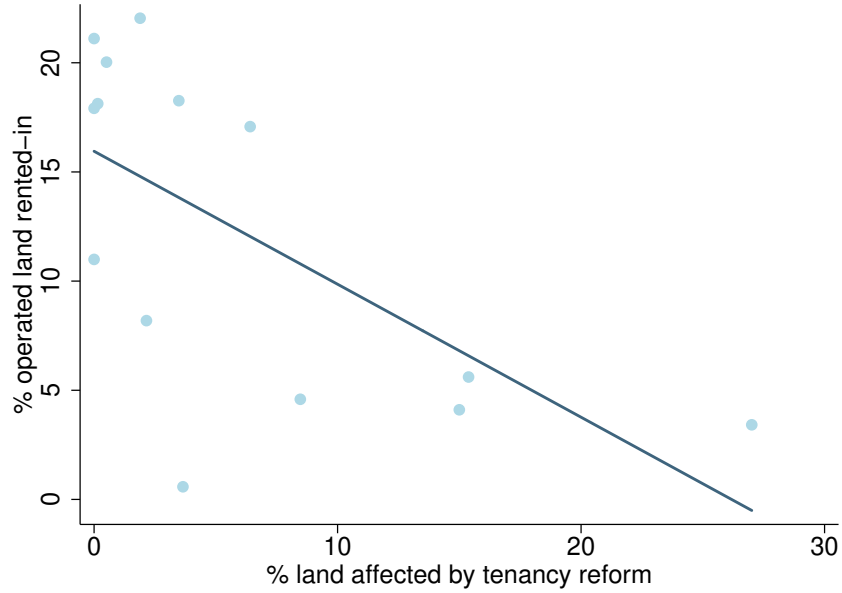


**Notes:** Panel A plots the share of operated land that is rented in against the share of farms that rent in land across states. Panel B plots the share of own land that that is rented out against the share of farms that rent out land across states in India. Data are from IHDS wave II 2011-12 ([Desai et al., 2012](#)).

We also find that rental market activity differs markedly across states. Figures 1 and 2 show the variation in rental market activity across states and how they correlate with institutional features at the state level. Figure 1 shows the extent of rental market activity across Indian states. Panel A shows the variation in the extensive and intensive margins of land rent-in activity. In several states, such as Tamil Nadu, Kerala, Maharashtra, less than 10% of farms rent-in land, and less than 5% of total operated land is rented in, whereas some states feature relatively active land markets such as Punjab where 23% of farms rent-in land and 22% of all cultivated land is rented. Panel B of Figure 1 shows similar differences in the extent of land rental market participation in renting out.

State differences in land rental market activity are associated with institutional features. Using state-level estimates of the share of arable land transferred as a result of tenancy legislation from [Kaushik and Haque \(2005\)](#), Figure 2 shows that states with higher shares of

Figure 2: Land Reforms and Rental Market Participation



**Notes:** Land rental market activity across states, measured by the percentage of cultivated land rented in, plotted against the share of agricultural land affected by land reforms from [Kaushik and Haque \(2005\)](#).

land affected by tenancy reforms tend to have less active rental markets. For instance, in the state of Maharashtra, where 27% of land was transferred as a result of tenancy legislation, only 3.4% operated land is rented in, whereas in Punjab less than 5% of the land was affected by tenancy reform and more than 20% of operated land is rented in. Similarly, ill-defined property rights combined with weak contract enforcement raise the effective transaction costs beyond the level implied by *de jure* regulation. Following [Boehm and Oberfield \(2020\)](#), we collect state-level estimates of the age of pending cases that pertain to land disputes from the National Judicial Data Grid ([Verma, 2018](#)). The age of pending cases differs substantially across states, from zero to more than 12 years. In Punjab and Haryana where the percentage of land rented in is high, the age of pending cases is below 2 years, whereas in states with a low level of land rented in such as Maharashtra, Tamil Nadu, and Gujarat, the age of pending cases is more than 6 years.

## 2.3 Measuring Farm Productivity

An important component for our analysis is farm total factor productivity which we measure using the farm output and input data. We assume that farms produce a homogeneous good and have a common production function that only differs in terms of their total factor productivity. The amount of real gross output produced by a farm household  $i$ , located in state  $s$ , and in year  $t$ ,  $y_{ist}$  is given by:

$$y_{ist} = a_{ist} \left[ \left( k_{ist}^\alpha \ell_{ist}^\beta n_{ist}^{1-\alpha-\beta} \right)^{1-\theta} m_{ist}^\theta \right]^\gamma; \quad \alpha, \beta, \theta, \gamma \in (0, 1), \quad (1)$$

where  $k_{ist}$  is the real capital stock,  $\ell_{ist}$  is operated land size,  $n_{ist}$  is total labor in hours,  $m_{ist}$  is real intermediate inputs, and  $a_{ist}$  is time-varying farm productivity. We measure  $a_{ist}$  as a residual from the production function with data on output and inputs. Note that the farm technology features decreasing returns to scale in variable inputs ( $\gamma < 1$ ), which is essential in determining the size of the farm ([Adamopoulos and Restuccia, 2014](#)). While specifying a common production function at the outset may seem restrictive, the evidence suggests that it generates a reasonable distribution of farm productivity, similar to that of an alternative approach of estimating the production function using panel data methods ([Aragón et al., 2022](#)). Our approach is restricted by the short time dimension of our panel data.

It is straightforward to show that while the farm-level production function features decreasing returns to scale on variable inputs, the aggregate production function in agriculture features constant returns to scale with the number of farms as an input ([Hopenhayn, 1992](#); [Adamopoulos et al., 2022](#)). Following this insight, we use aggregate expenditure shares of revenue of factor inputs for all farms in the data to calibrate the production function parameters, an approach that is common in the macroeconomics literature ([Valentinyi and Herrendorf, 2008](#); [Adamopoulos and Restuccia, 2014](#)). Using the data from IHDS wave I, we find that the expenditure shares of capital, land, labor, and materials are 0.11, 0.25, 0.19, and 0.20, respectively. These parameters imply from equation (1) that  $\alpha = 0.20$ ,  $\beta = 0.43$ ,

$\theta = 0.28$ , and  $\gamma = 0.75$ . The resulting parameter estimates are broadly consistent with estimates from other studies ([Adamopoulos et al., 2022](#); [Aragón et al., 2022](#); [Chen et al., 2022](#)). Nevertheless, we discuss below robustness of our results with respect to the value of decreasing returns to scale parameter  $\gamma$ .

Using the estimated production function parameters, farm total factor productivity  $a_{ist}$  is measured as a residual from equation (1) for each farm and survey wave. Recognizing that the residual from the production function in each year is potentially comprised of a permanent component of farm productivity that we are interested in measuring, as well as a stochastic component that varies every year, we back out the permanent component of farm productivity using the two-wave panel data with farm and time fixed effects. In particular, we follow [Adamopoulos et al. \(2022\)](#) to decompose the logarithm of farm TFP ( $\ln a_{ist}$ ) as follows:

$$\ln a_{ist} = \ln a_{is} + \ln a_t + \nu_{ist}, \quad (2)$$

where  $\ln a_t$  is a year fixed effect component that captures time-varying shocks to productivity (e.g., weather) that are common across farmers,  $\ln a_{is}$  is a household farm fixed effect component that captures persistent productivity differences across farmers including state level differences, and  $\nu_{ist}$  is an error term that reflects farmer- and time-specific productivity shocks including the possibility of additive measurement error. We estimate equation (2) using panel data methods to extract the household farm fixed effect  $\ln a_{is}$  which is inclusive of location-level differences (e.g. land quality). We then remove location-level differences by regressing  $\ln a_{is}$  on location dummies and extracting the residual. Using the state location information of each farmer, denoted by  $s$ , we estimate

$$\ln a_{is} = \ln a_s + \ln z_{is},$$

where the predicted error term  $\ln z_{is}$  is our estimate of permanent farm-specific TFP after removing farm-specific time varying shocks to the farm residual, as well as a state-specific



component.<sup>2</sup>

Table 2: Farm Total Factor Productivity

	Distribution of log Farm TFP ( $\ln z_{is}$ )		
	SD	90-10	75-25
India	0.62	1.58	0.82
States:			
[AP] Andhra Pradesh	0.62	1.60	0.89
[AS] Assam	0.71	1.82	0.76
[BR] Bihar	0.52	1.32	0.72
[GJ] Gujarat	0.85	2.38	1.21
[HR] Haryana	0.61	1.59	0.89
[KA] Karnataka	0.78	2.10	1.13
[KL] Kerala	0.89	2.29	1.45
[MP] Madhya Pradesh	0.59	1.54	0.83
[MH] Maharashtra	0.64	1.75	0.83
[OR] Orissa	0.54	1.35	0.73
[PB] Punjab	0.49	1.17	0.66
[RJ] Rajasthan	0.76	2.02	1.07
[TN] Tamil Nadu	0.83	2.38	1.00
[UP] Uttar Pradesh	0.51	1.36	0.70
[WB] West Bengal	0.37	0.97	0.48

**Notes:** Statistics on the distribution of log farm TFP  $\ln z_{is}$  are the standard deviation and the difference between the 90 and 10 percentiles and the 75 and 25 percentiles of the productivity distribution in India and in each state.

Table 2 summarizes the distribution of farm productivity ( $\ln z_{is}$ ) for India as a whole and for each state in our sample. There is substantial dispersion in farm productivity in all states, with a standard deviation of log farm productivity of 0.37 in West Bengal and 0.89 in Kerala. For India, the standard deviation of log farm productivity is 0.62. Comparatively, these dispersion measures of farm productivity are consistent with findings for the agricultural sector in other contexts such as a standard deviation of log farm productivity of 0.93 in

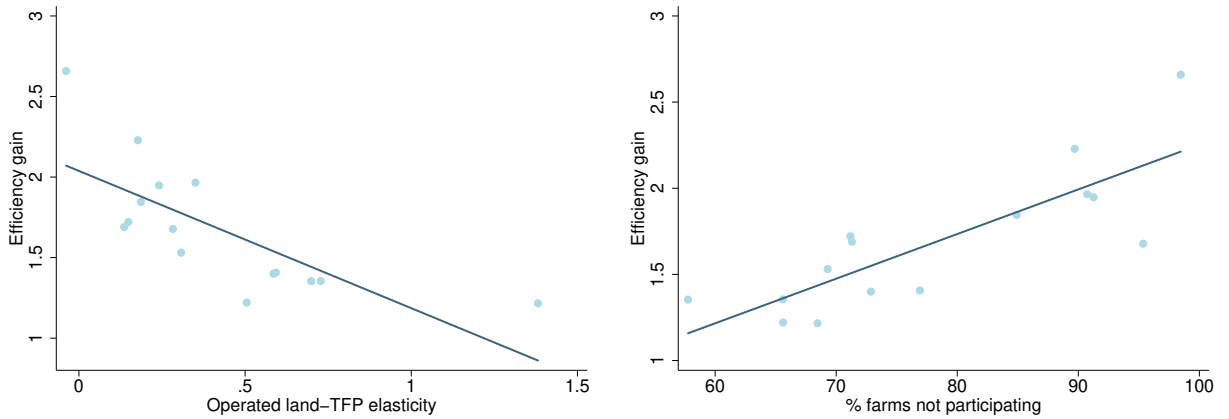
<sup>2</sup>We continue to denote farm productivity  $z_{is}$  with index  $s$  to indicate that farm  $i$  produces in state  $s$  even though productivity  $z_{is}$  is devoid of state-level differences.

Malawi (Chen et al., 2023) and 0.64 in China (Adamopoulos et al., 2022); as well as findings in the range of 0.85-1.16 for other sectors such as manufacturing plants in China, India, and the United States (Hsieh and Klenow, 2009). Despite the limited time dimension of the panel data, the variance of the permanent component of log farm productivity,  $\ln z_{is}$ , in our data is about 60 percent of the cross-sectional variance of  $\ln a_{ist}$ , hence, controlling for variation across time and space reduces the cross-sectional dispersion of farm productivity by about 40 percent.

## 2.4 Misallocation and Land Rentals

Using our estimates of farm productivity, we now provide a characterization of misallocation in agriculture across Indian states and its connection with the extent of land rental markets, a connection we assess in more detail in our quantitative analysis.

Figure 3: Misallocation and Land Rentals



**Notes:** Operated land-TFP elasticity refers to the elasticity of operated land with respect to our measure of farm TFP. Efficiency gain refers to the ratio of aggregate efficient output relative to aggregate actual output, where output is modeled as productivity times a composite land input as defined in section 3. Circles are the data in each state in our sample and the solid line is the best fit.

Figure 3 reports two commonly used measures of misallocation in the literature: the productivity gradient of cultivated land in farms, measured by the elasticity of cultivated land on farm productivity, and the aggregate productivity gain from efficient factor reallocation

across farms. Appendix C provides a detailed characterization of the efficient allocation and a definition of efficiency gains. In particular, note that the efficient allocation implies a high land-productivity elasticity, hence a low elasticity is associated with misallocation of resources. Panel A in Figure 3 shows that these two measures of misallocation are strongly related and that there are important differences in misallocation across states. For instance, Punjab features the lowest efficiency gain of 1.25-fold (a 25% increase from efficient reallocation) and the highest land-productivity elasticity, whereas several other states feature efficiency gains higher than 1.8-fold and land-productivity elasticity near zero. We also note that states differ slightly in the relationship between land endowment and farm productivity, with Tamil Nadu featuring the lowest correlation (in logs) of  $-0.04$ , most other states with correlation between 0.1 and 0.3, and Punjab with the higher correlation of 0.55. This weak correlation of land endowments and farm productivity implies a need for active land rental markets to achieve a more efficient allocation of land across productive uses.

Panel B in Figure 3 shows that states with less active land rental markets (higher rates of non participation) feature higher misallocation in agriculture. A similar pattern arises when using the percentage of land not rented as a measure of the extent of rental markets.

We use this suggestive evidence connecting the extent of land rental markets with misallocation across Indian states to develop a model of distorted rental markets in the next section in order to quantify the role of land market distortions on agricultural productivity.

## 2.5 Mismeasurement

Estimates of productivity and misallocation are subject to several potential concerns of measurement and misspecification (Bils et al., 2021; Gollin and Udry, 2021). Invariably the data may be measured with error and our analysis makes important abstractions that may create bias. Nevertheless, we emphasize several features of our analysis that provide some perspective on the extent of mismeasurement.

First, our analysis focuses on the household farm as unit of production instead of a plot operated by the farm. Measuring productivity at the farm level has been shown to greatly reduce observed plot-level productivity dispersion and to generate a more accurate assessment of misallocation in agriculture (Aragón et al., 2024). Second, our analysis uses the panel dimension of the data to remove transitory variation in productivity, including potential additive measurement error (Bils et al., 2021). Moreover, we focus on reallocation within states to minimize the impact of state-level differences. We have shown that removing transitory variation and state-level differences contribute to a substantial 40 percent reduction in productivity dispersion in our baseline measures compared to cross-sectional measures of productivity. Third, our analysis of misallocation restricts variation in input ratios across farms which may be due to farmers using alternative technologies or making different cropping choices. Appendix C shows that efficiency gains with land input is a conservative measure of misallocation representing 75% of the efficiency gains when using all inputs. We consider potential variation in production technologies across crops and how they might affect estimated farm productivity in Appendix B.2. We use crop-level output information to classify farms that produce more than 50 percent of their estimated revenue from a single crop and re-estimate factor shares by crop. We find that factor shares are roughly similar across the major crops produced in India, and that the implied farm productivity with crop-specific factor shares are highly correlated with our baseline measure (average correlation of 93 percent across farms within states). We also restrict reallocation within districts in a state and reallocation across farms producing similar crops, finding similar reallocation gains (see Appendix C).

Fourth, we also explore variation in our estimate of the decreasing returns to scale parameter  $\gamma$  on farm productivity and measures of misallocation. We find that the quantitative effect of changes in  $\gamma$  on the distribution of TFP is quite small, owing to the fact that the dispersion in land input across farms is much smaller than the dispersion of output. For instance, the dispersion in farm-level TFP in India measured by the standard deviation of log, changes

from 0.626 with our baseline  $\gamma = 0.75$  to 0.638 with  $\gamma = 0.70$  and 0.617 with  $\gamma = 0.80$ . This implies a small variation in the estimated elasticity of farm-level land input to TFP, and hence the implied elasticity of distortions with respect to TFP as we discuss in detail in Appendix C. Overall, we find that the extent of misallocation in Indian states is fairly robust to changes in  $\gamma$ , consistent with the findings in other contexts in the related literature (Adamopoulos et al., 2022; Chen et al., 2023). More importantly, our focus is on differences in misallocation across Indian states, a relative ranking that is invariant to the value of  $\gamma$ .

### 3 Model

To assess the quantitative relevance of land rental market activity on agricultural productivity across Indian states, we develop a model of agricultural production with heterogeneous farms and distorted land rental markets, building on Deininger and Nagarajan (2010) and Adamopoulos and Restuccia (2014).

#### 3.1 Description

We consider an agricultural economy that comprises  $S$  regions called states indexed by  $s$ . Each state  $s$  is endowed with an aggregate amount of land  $L_s$  and a finite number of farm households  $F_s$  indexed by  $i$  that differ in their farming productivity  $z_{is}$ , land endowment  $\bar{\ell}_{is}$ , and land distortions that we describe below. Individual farms produce a homogeneous output good using the following decreasing returns to scale technology,

$$y_{is} = z_{is} \ell_{is}^\gamma, \quad 0 < \gamma < 1,$$

where  $\ell_{is}$  is the amount of land operated by the farm. We normalize the price of the output good to one. There is no trade or factor mobility between states. The model is static and for ease of exposition we abstract from time subscripts.

We focus on the institutions that affect land rental markets across states and model the effect of these institutions through land distortions. We argue that a suitable approach to capture the effect of these institutions on farm decisions is for land distortions to impact all other inputs so that input ratios are unaffected. We follow this approach in specifying the model below. It is straightforward to show that this approach is equivalent to modeling land as a composite input in production since all the input ratios are constant (see Appendix B.2) and that it delivers a conservative measure of misallocation (see Appendix C). The evidence from many different contexts is supportive of this approach (Hsieh and Klenow, 2009; Chen et al., 2023; Adamopoulos et al., 2022; Chen et al., 2022).

We assume farmers cannot sell their endowed land so that land reallocation occurs only through rentals. While this assumption may seem restrictive, in practice there are very few land sale transactions in India. In our data, only 3% of farming households purchased the land they own, while 95% acquired the land through family. In contrast, about 10% of households participate in the rental market in either wave. Farmers can rent land to ( $\ell_{is}^{out}$ ) or from ( $\ell_{is}^{in}$ ) other farmers, but face implicit farmer-specific transaction prices  $q_{is}^{in}$  and  $q_{is}^{out}$  per unit of land rented in and rented out.

For ease of exposition and without loss of generality, we model farm-specific land rental prices as effective taxes or subsidies on the rental price of land  $q_s$ . In practice, the wedges to land rental rates stand in for a myriad of explicit and implicit taxes, regulations, and features of land institutions in each state that affect land transactions. We distinguish between two components of land distortions: a novel state-level rental barrier common among farmers in a state that creates a wedge between the land rent-in and rent-out rates  $\tau_s$  and an idiosyncratic (farm-level) component of distortions that differs across farmers in a state which we denote by  $\tau_{is}$  as is standard in most of the misallocation literature. Hence, effective land rental prices are given by:

$$q_{is}^{in} = q_s(1 + \tau_{is}), \quad q_{is}^{out} = \frac{q_{is}^{in}}{\tau_s}, \quad \tau_s \geq 1.$$

A key feature of this framework is that the state-level rental barrier  $\tau_s$  allows the model to generate non-participation in the land-rental market, a prevalent feature in our data that varies systematically across states.

### 3.2 Decentralized Allocation

For each state, given farm productivity  $z_i$ , land endowment  $\bar{\ell}_{is}$ , price  $q_s$ , and land-market distortions  $(\tau_{is}, \tau_s)$ , farms choose the operational scale, that is the amount of cultivated land  $\ell_{is}$ , which is equal to the amount of endowed land  $\bar{\ell}_{is}$  plus land rented in  $\ell_{is}^{in}$  minus land rented out  $\ell_{is}^{out}$ , to maximize profits:

$$\max_{\{\ell_{is}, \ell_{is}^{out}, \ell_{is}^{in} \geq 0\}} \pi_{is} \equiv z_i \ell_{is}^\gamma - q_s(1 + \tau_{is}) \ell_{is}^{in} + \frac{q_s(1 + \tau_{is})}{\tau_s} \ell_{is}^{out}, \quad (3)$$

subject to

$$\ell_{is} = \bar{\ell}_{is} + \ell_{is}^{in} - \ell_{is}^{out}.$$

A *competitive equilibrium* is a land rental price  $q_s$  and allocations  $\{\ell_{is}, \ell_{is}^{in}, \ell_{is}^{out}\}$  such that: (i) Given prices, farmers' allocations maximize profits, i.e., solve the problem in equation (3), and (ii) the land market clears, i.e.,  $\sum_i \ell_{is} = L_s$ . Appendix D.1 describes the procedure we use to solve for the competitive equilibrium in each state.

Within a state, given farm productivity, land endowment, and rental prices, farm land choices  $\{\ell_{is}, \ell_{is}^{in}, \ell_{is}^{out}\}_{i=1}^{F_s}$  are characterized by:

$$q_s(1 + \tau_{is}) \geq MPL_{is} = \frac{q_s(1 + \tau_{is})}{\tau_s} \quad \text{if } \ell_{is}^{in} = 0 \text{ and } \ell_{is}^{out} > 0, \quad (4)$$

$$q_s(1 + \tau_{is}) = MPL_{is} \geq \frac{q_s(1 + \tau_{is})}{\tau_s} \quad \text{if } \ell_{is}^{in} > 0 \text{ and } \ell_{is}^{out} = 0, \quad (5)$$

$$q_s(1 + \tau_{is}) \geq MPL_{is} \geq \frac{q_s(1 + \tau_{is})}{\tau_s} \quad \text{if } \ell_{is}^{in} = 0 \text{ and } \ell_{is}^{out} = 0, \quad (6)$$

where  $MPL_{is} = \gamma z_{is} \ell_{is}^{\gamma-1}$  is the marginal product of land of farm  $i$  in state  $s$ . In equilibrium,

the first order conditions in equations (4) and (5) are binding for farmers participating in the land rental market, that is farmers rent in or rent out land up to the point where their marginal product of land equals the effective rental prices they face. We exploit this feature of the model and the fact that our data distinguish between own and rented land as well as rental market participation, to separately identify state-level rental barriers  $\tau_s$  and idiosyncratic distortions  $\tau_{is}$  as we discuss below.

### 3.3 Discussion

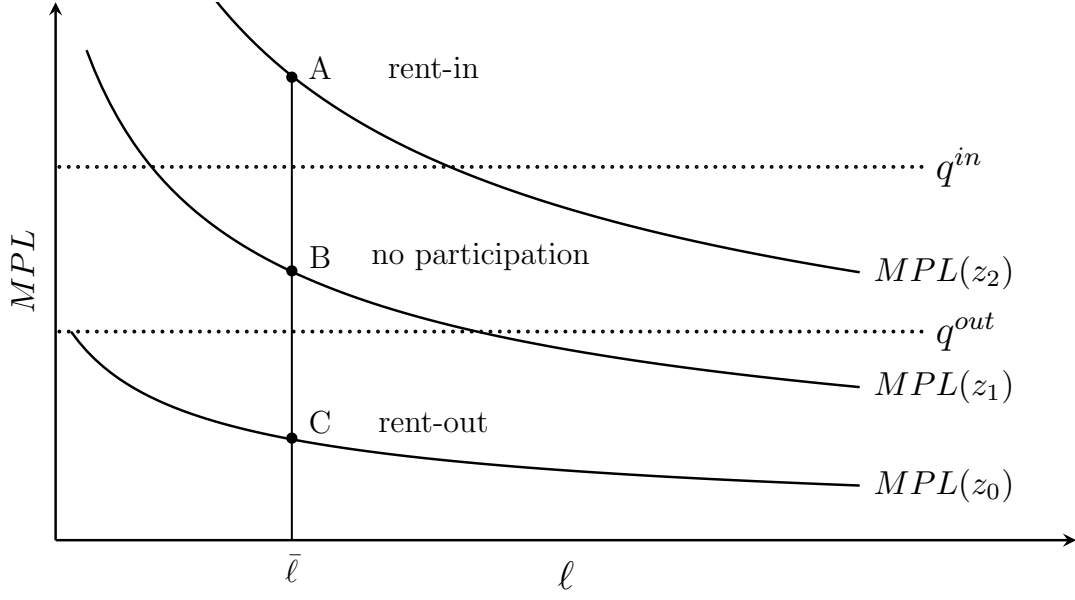
It is instructive to note in the characterization of operational scales (farm size) that without distortions, that is when  $\tau_s = 1$  and  $\tau_{is} = 0$  for all  $i$ , operated land  $\ell_{is}$  in equilibrium is such that the marginal product of land for each farmer in a state is equalized to the common price  $q_s$ . This implies in our model that operated land is proportional to farm productivity  $z_{is}$  with elasticity  $1/(1 - \gamma)$ , irrespective of the land endowment (see Appendix C). Moreover, in this case all farmers participate in the land rental market (save for a measure zero case where optimal farm size is the same as the land endowment for an individual farmer).

**Role of state-level rental barrier  $\tau_s$ .** Recall that  $\tau_s > 1$  creates a wedge between the land rent-in and rent-out rates. Figure 4 illustrates how farm productivity, land endowment, and distortions influence farm operational scale and hence land allocations and land rental-market participation. The x-axis represents the farm operational scale (land size  $\ell$ ) and the y-axis the marginal product of land and land rental prices. The solid lines represent the marginal product of land schedule for farmers with different total factor productivity  $z$ , with more productive farmers featuring higher marginal product of land schedules ( $z_2 > z_1 > z_0$ ).

We want to establish that the rental barrier  $\tau_s > 1$  implies an inaction zone where farmers choose not to participate in the land rental market and simply operate the farm with their land endowment. Assuming that farmers are endowed with the same amount of land  $\bar{\ell}$



Figure 4: Characterizing Land Rental-Market Participation



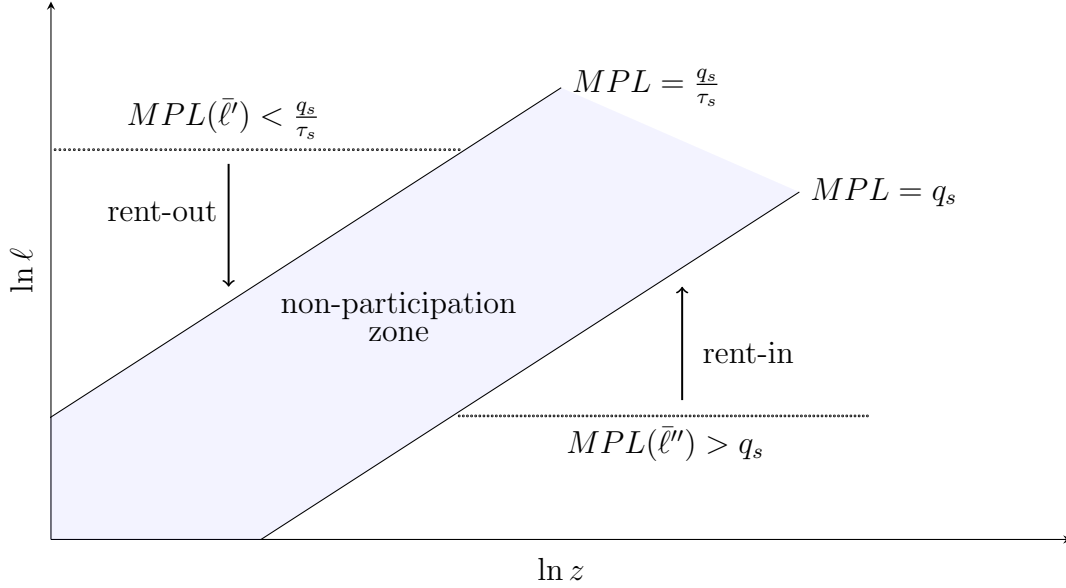
and are facing the same land rental prices  $(q^{in}, q^{out})$ , Figure 4 displays the optimal farm allocation in three different cases. First, if the marginal product of land at the endowment is higher than the cost of renting in land, point A for farmer with productivity  $z_2$ , then the farmer rents land (increasing operational scale) until the point where the marginal product of operated land equalizes the rent in price  $q^{in}$ . Second, if the marginal product of endowed land is below the rent out price, point C for farmer with productivity  $z_0$ , then the farmer rents out land until the point where the marginal product of operated land equalizes the rent out price  $q^{out}$ . Third, if the marginal product of endowed land is between the rent in and rent out rates, point B for farmer with productivity  $z_1$ , then the farmer does not to participate in the rental market and operates the land endowment  $\bar{\ell}$ . Hence, when  $\tau_s > 1$ , there is an inaction zone in land market participation where a subset of farmers simply operate their land endowment. Moreover, a higher rental barrier  $\tau_s$ , other things equal, imply a larger gap between the rental rates and a higher proportion of farmers not participating in the land rental market since the zone of inaction is larger. Land rental market participation is a key moment determining the wedge between the effective land rental rates, a feature we exploit

in our quantitative strategy to determine  $\tau_s$  across states.

Figure 5 illustrates the stylized relationship between operated land and farm productivity for all farmers. The two solid lines represent the land demand for farms facing the rent in and rent out rates, where  $\tau_s > 1$  implies a wedge between the rental rates, which in turn creates a wedge between the operated land demands of farmers renting in and renting out. The horizontal distance between the rent-in and rent-out land demands determines the inaction zone, the range of farm productivity for which farmers simply operate their land endowment. Figure 5 depicts behavior of farmers with different land endowments. At high land endowment,  $\bar{\ell}'$ , farmers with low productivity rent out land until they reach an operational scale that makes their marginal product of land equal to their rental rate,  $q_s/\tau_s$ . However at high enough farm productivity, the farmer would prefer to not participate in the rental market. At low land endowment,  $\bar{\ell}''$ , farmers with low productivity do not participate in the rental market, but high productive farmers demand more land. These farmers rent in land until they reach an operational scale where the marginal product of land equals the land rent-in rate  $q_s$ . Hence, when farmers differ also in land endowments, there is a set of inaction zones, creating a “thick” positive relationship between farm size and productivity.

In practice, non-participation also depends on idiosyncratic distortions and hence in general  $\tau_s$  cannot be measured independently of other model components as we discuss below. Nevertheless, we provide suggestive empirical evidence that  $\tau_s$  differs across states in India. In particular, the model implies that the larger  $\tau_s$  is, other things equal, the larger the non-participation. This implies a larger gap between the average marginal product of endowed land between farmers that rent-in and farmers that rent-out land. The average reduces the influence of idiosyncratic components of distortions. Note that in the case where land endowments are the same across farmers and there are no idiosyncratic distortions, the marginal product of endowed land reflects farm productivity only, those that rent-in have higher productivity than those that rent-out, and the larger the non-participation, the larger the productivity gap between the two groups of land market participants.

Figure 5: Stylized Operated Land and Farm Productivity

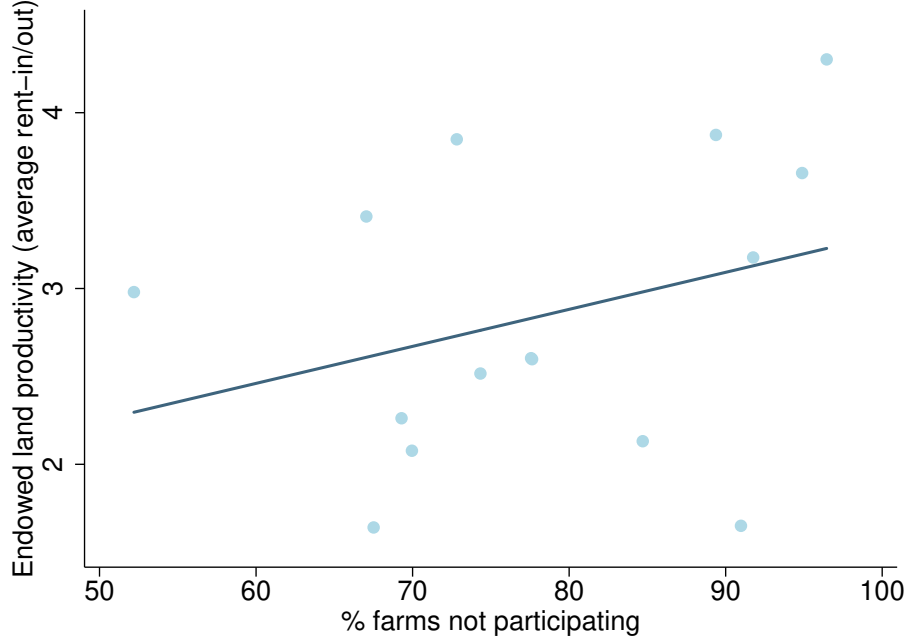


**Notes:** Stylized relationship between land operational scale (farm size)  $\ell$  and farm productivity  $z$  (in logs) for farmers that differ on their land endowment  $\bar{\ell}$  but face common effective land rental rates  $q_s^{in}, q_s^{out}$  and rental barrier  $\tau_s$ .

We document the evidence on the average land productivity gap between those renting in and those renting out in the data for each state in Figure 6. It shows that states with larger farm non-participation in land rental markets feature a larger gap in the average marginal products of endowed land between farmers renting in and out.

**Role of idiosyncratic distortions  $\tau_{is}$ .** The challenge to fully characterize land-market participation from the data is that even though farm productivity and land endowments are observable, distortions affecting idiosyncratic effective rental rates are not, and hence, idiosyncratic distortions can be such that any farmer regardless of productivity or land endowment, rents in, rents out, or does not participate in the land market. To overcome this challenge, our quantitative analysis imposes specific functional forms on the process of idiosyncratic distortions so that moments of land operational scale together with land market participation identify the key parameters of interest.

Figure 6: State-level Wedge and Rental Market Non Participation

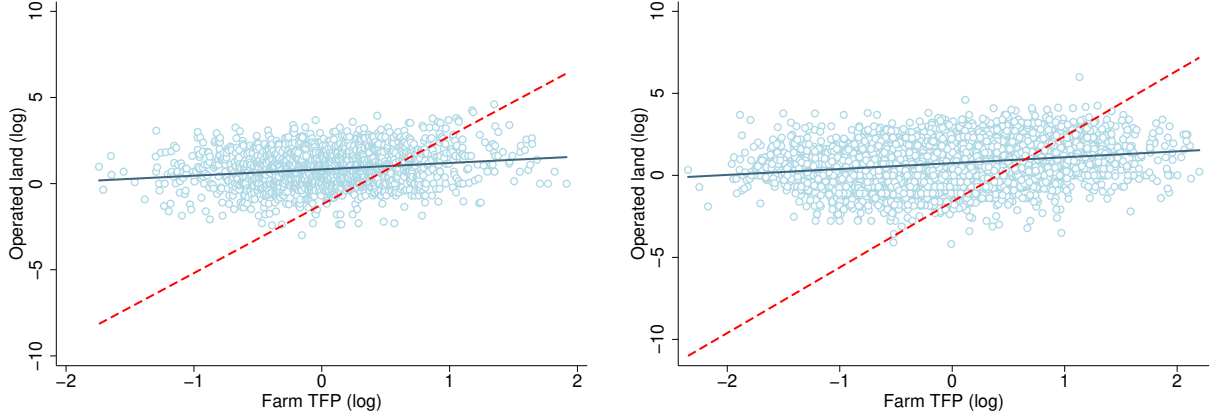


**Notes:** Average marginal product of endowed land, ratio of farms that rent-in to farms that rent-out. This relative measure of land productivity proxies for the magnitude of the state-level wedge  $\tau_s$  and is increasing with the percentage of farmers that do not participate in the land rental market.

To illustrate how additional moments on the operational scale (farm size) are informative, consider that in the stylized case discussed earlier where rental rates are the same across farmers (see Figure 5), land operational scales have two key properties: (1) land size is increasing in farm productivity for farmers participating in the rental market (those renting in and renting out) and (2) selection into non-participation implies that even for farmers not participating in the land rental market, land size features a thick positive relationship with farm productivity. Therefore, data on farm size by productivity provide evidence of the extent to which farmers are effectively facing the same or different rental prices. That is, moments associated with the relationship between land size (or the marginal product of land) and productivity in the data provide identification of the variation in effective rental prices across farmers.

Figure 7 documents the relationship between land size and farm productivity among two

Figure 7: Operated Land and Farm Productivity



**Notes:** Panel A reports the operated land and farm productivity (in logs) for farmers participating in the land rental market, whereas Panel B reports the same for farms not participating in the land rental market. Circles represent the data from all 15 states in our data sample. Solid lines represent the best fit, whereas dashed lines represent the efficient  $1/(1 - \gamma)$  slope for reference.

types of farmers. Panel A documents the relationship for farmers that participate in the land rental market for all India, whereas Panel B documents the relationship between farm size and productivity for farmers that do not participate in the land rental market in India. In the absence of idiosyncratic distortions  $\tau_{is}$ , we expect a positive relationship for farmers participating in the land rental market (solid lines in Figure 5), whereas in the data the relationship is fairly flat (panel A). We also expect no dispersion in land size for farmers with the same TFP participating in the rental market, so again dispersion in land size among farms with the same TFP provides evidence of dispersion in effective rental rates.

For farmers not participating in the rental market, farm size is the land endowment, but without idiosyncratic distortions, because of selection we expect a positive diagonal band between farm size and productivity (shaded region in Figure 5). However, in the data the band is again fairly flat (panel B), suggesting differences in effective rental prices across farmers affecting land market participation. Moreover, the range in farm productivity for non-participants is as large or larger than for farmers participating in the land rental market, again suggesting a lack of selection on farm productivity for non-participants.

### 3.4 Parametrizing Idiosyncratic Distortions

For farmers participating in the land rental market we can infer their idiosyncratic distortions using the binding first order conditions in equations (4) and (5). These conditions show that the marginal product of land ( $MPL = \gamma y/\ell = \gamma z\ell^{\gamma-1}$ ) for each farmer that participates in the rental market is proportional to their idiosyncratic distortions,

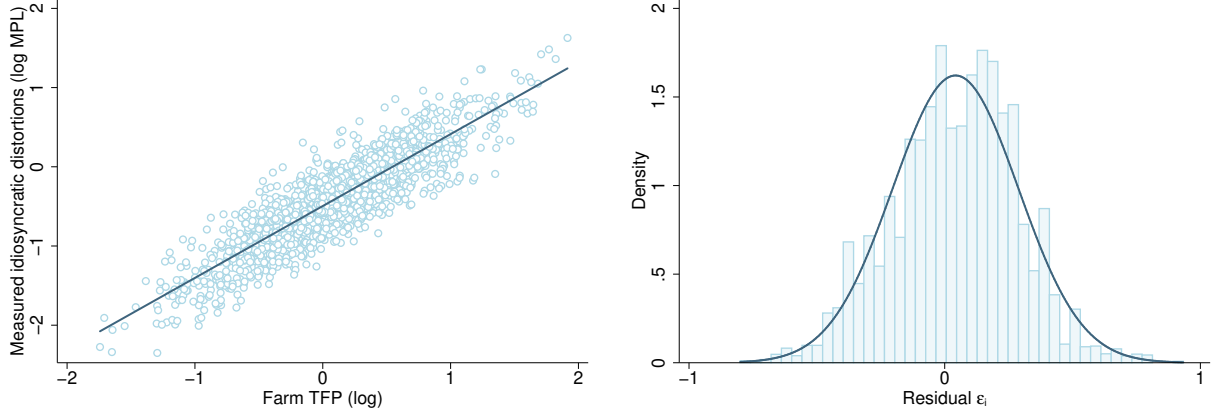
$$MPL_{is} \propto (1 + \tau_{is}),$$

with the constant of proportionality being different between those renting in and renting out by the constant  $\tau_s$ . Note that this characterization of distortions is similar to the identification of wedges in [Hsieh and Klenow \(2009\)](#). As a result, we measure idiosyncratic distortions for farmers participating in the land rental market as the residual from a regression of  $\log MPL_{is}$  on a dummy for farmers renting out land, and characterize its properties. Our objective is to motivate an empirically appropriate functional form for idiosyncratic distortions, not to estimate them directly. The reason is that while we can back out idiosyncratic distortions faced by farmers who participate in the rental market, up to a constant, directly from data on  $MPL$ 's, we cannot do the same for the large share of farmers who do not participate in land rental markets. We therefore use the characterization of distortions for rental market participants to motivate a parametric form of distortions faced by all farmers.

Figure 8, panel A, documents our measure of idiosyncratic distortions (in logs) for farmers participating in the land rental market in all states in India against farm productivity (in logs). We find a strong positive relationship between the two indicating that more productive farmers face larger distortions to their effective rental prices. Regressing log idiosyncratic distortions on log farm productivity, we find that this systematic component accounts for a large portion of the variation in idiosyncratic distortions, with an R-squared of more than 87%. Moreover, the residual from this regression is well approximated by a normal distribution, as we document in panel B. Appendix C discusses the robustness of the relationship

between farm-level land input and TFP in Figure 7A and the implied distortions in Figure 8A to production function parameters.

Figure 8: Idiosyncratic Distortions and Farm Productivity



**Notes:** Panel A reports for farmers that participate in the land rental market, idiosyncratic distortions measured by the marginal product of land (in logs) against farm productivity (in logs). Circles represent the data for farm participants in the rental market for all 15 states in our sample. The solid line is the best fit. Panel B reports the histogram of the residuals from regressing idiosyncratic distortions on farm productivity.

This observation for farmers participating in the land rental market suggests that idiosyncratic farm-level distortions can be characterized as follows:

$$\ln(1 + \tau_{is}) = \theta_s \ln z_{is} + \epsilon_{is},$$

$$\epsilon_{is} \sim N(0, \sigma_{\epsilon s}^2), \quad \text{i.i.d. across farms,}$$

where  $\theta_s$  controls the elasticity of distortions with respect to farm productivity and  $\sigma_{\epsilon s}$  controls the dispersion in distortions not generated by  $\theta_s$ . This parametrization of distortions is known to generate a good fit with micro data in other contexts ([Restuccia and Rogerson, 2017](#); [Restuccia, 2019](#)).

We emphasize that this parametrization of distortions is required for our quantitative analysis since we do not know the idiosyncratic distortions faced by farmers that do not participate in the land rental market. Moreover, the values of the parameters of idiosyncratic distortions  $\theta_s, \sigma_{\epsilon s}$  cannot be directly estimated from our data because selection into renting can affect

the specific estimates, and this bias is likely to differ across states. Our approach instead is to calibrate the parameters of distortions which include the state-level rental barrier  $\tau_s$  to match moments of land market participation and farm operational scales.

## 4 Quantitative Analysis

We estimate land-market distortions by calibrating the parameters of distortions  $(\tau_s, \theta_s, \sigma_{\epsilon s})$  to match data moments for each state, evaluate the empirical fit of the model in non-targeted moments, and provide our main results by conducting a set of counterfactual experiments.

### 4.1 Calibration

Given our parametric assumptions, land-market distortions are characterized by (1) the state-level wedge between land rental rates  $\tau_s$ , (2) the elasticity of distortions with respect to farm productivity  $\theta_s$ , and (3) the standard deviation of the random component of distortions  $\sigma_{\epsilon s}$ . The solution of the estimation involves drawing a value of  $\epsilon$  for each farmer in the data from the normal distribution given  $\sigma_{\epsilon}$ , solving the equilibrium of the model (i.e., solving for the price of land  $q_s$  that clears the land market), and constructing moments from the model that depend on the three unknown population parameters  $(\tau_s, \theta_s, \sigma_{\epsilon s})$ . We use the data counterpart of these moments to estimate the distortion parameters. As motivated in our previous section, the moments we construct relate to the extent of farmer's land market participation and features of the dispersion of the marginal product of land across farmers which depend the farm's operational scale. In particular, our target moments are: (i) the share of farmers not participating in the land rental market, (ii) the covariance between the marginal product of land and farm productivity across farmers, and (iii) the variance of the marginal product of land across farmers. We provide more details on this procedure in [Appendix D.2](#) and a robustness analysis in [Appendix D.3](#).

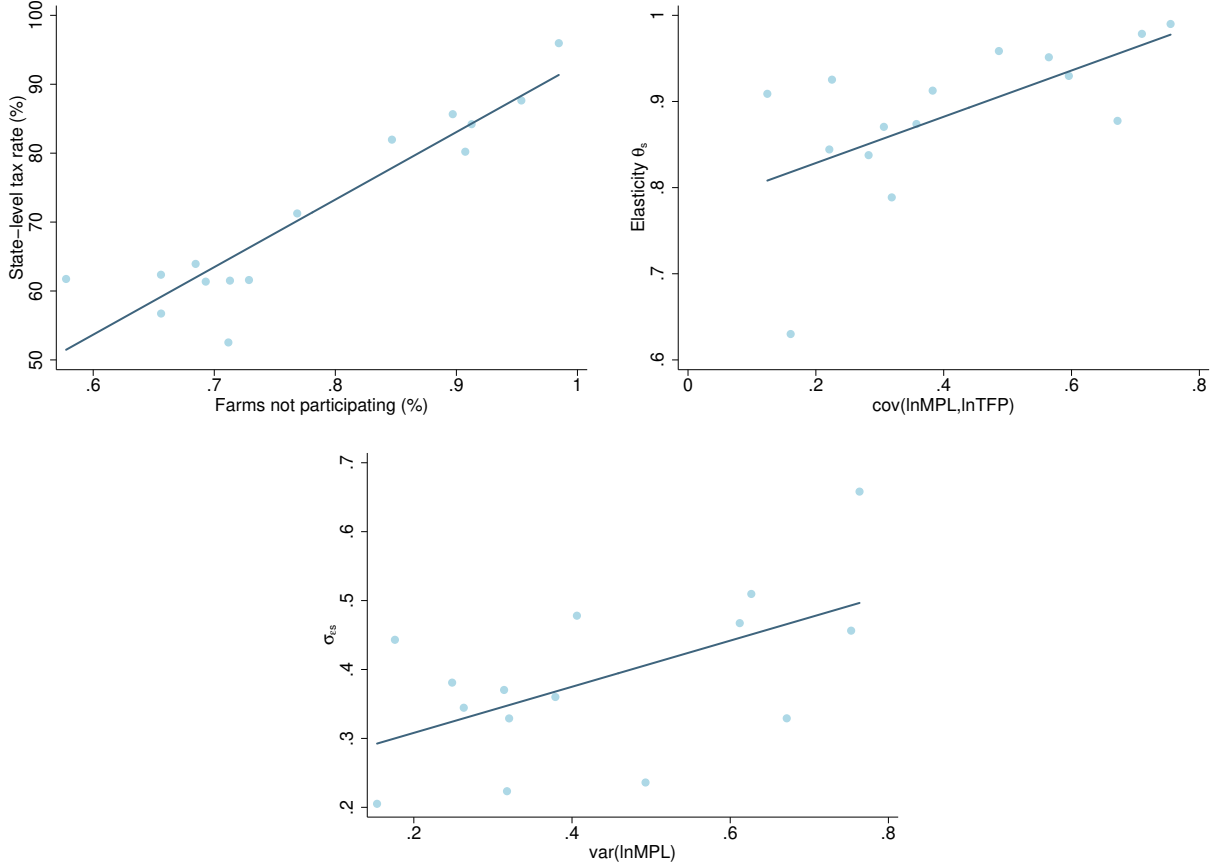


Figure 9 reports the estimated parameter values for  $\tau_s$ ,  $\theta_s$ , and  $\sigma_{\epsilon s}$  in each state against the respective moments that provide their identification in the data. We report the parameter  $\tau_s$  as a tax rate on the rental rate or equivalently the tax on the rental income received by farms renting out land, that is we report  $(1 - 1/\tau_s)$ . We note as expected the close connection between the state-level rental barrier and rental market non-participation across states in panel A. We also note the much higher elasticity of distortions with respect to farm productivity in most states relative to Punjab (panel B) and the somewhat larger dispersion in the random component of distortions in states where the dispersion in the marginal product of land across farms is high (panel C).

Our estimates indicate that there is a systematic pattern of land distortions and rental markets across states: land distortions are less severe in states with more active rental markets. The estimates of  $\tau_s$  for example imply a range for the effective tax rate on the rent-in rate from 53 percent in Assam to 96 percent in Tamil Nadu. The estimates of  $\theta_s$  range from 0.98 in Kerala and 0.97 in Tamil Nadu, to 0.63 in Punjab which has the highest correlation between farm size and farm productivity. This wide range of elasticity estimates is consistent with evidence of high elasticities in developing countries such as China, Malawi, Ethiopia, and Uganda where land markets are severely restricted, and lower elasticities in developed countries such as the United States (Chen et al., 2023; Adamopoulos et al., 2022; Chen et al., 2022; Aragón et al., 2022; Rada and Fuglie, 2019). These patterns suggest that rental barriers prevent active participation in rental markets across states and that idiosyncratic frictions tend to systematically constrain the more productive farmers that would operate much larger farms in the absence of distortions.

**Model fit.** We have taken a parsimonious parametric approach to capturing land market distortions in the data, summarized by three parameters: the productivity slope and variance of farm-specific distortions, and a state-level barrier to leasing land. We illustrate that this approach successfully captures other patterns of land allocations across states in the micro

Figure 9: Identification of Land Rental-Market Distortions

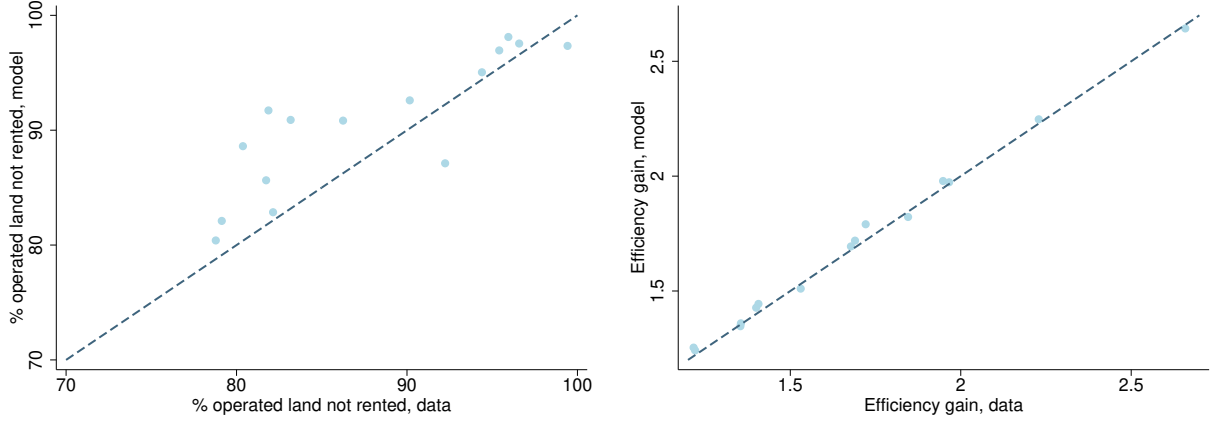


**Notes:** Panel A reports the estimated state-level rental barrier  $\tau_s$  as a tax rate on the rent-in rate, i.e.,  $\text{tax} = (1 - 1/\tau_s)$  against the percentage of farms not participating in the land rental market. Panel B reports the estimated idiosyncratic distortions elasticity  $\theta_s$  against the covariance between the marginal product of land and farm productivity (in logs). Panel C reports the estimated distortions dispersion parameter  $\sigma_{\epsilon s}$  against the variance of the (log) marginal product of land. Circles represent the 15 Indian states in our sample and the solid lines are the best fit relationship.

data not targeted in the calibration.

While the model is calibrated to match the percentage of farmers not participating in the land market, Figure 10, panel A, reports the percentage of land not rented in each state as an alternative metric of the extent of land markets in each state both in the model and the data. Even though the model is not calibrated to match this statistic, the model matches relatively well the data in most states. Another summary metric of the fit of the model in each state is the implied efficiency gain since this statistic is a function of the land allocations implied by the model. Figure 10, panel B, plots the efficiency gain in each state from the estimated

Figure 10: Land Allocations and Efficiency Gains, Model versus Data



**Notes:** Panel A plots the percentage of operated land not rented in each state in the model (unweighted average of 100 simulations) and the data. Panel B plots efficiency gains (ratio of efficient to actual output) in each state in the model (unweighted average of 100 simulations) and the data. Dots represent states. Dashed lines represent the 45 degree line in both panels.

model against the gains in the data. Note that given data on farm productivity and total cultivated land in each state, the efficient output is exactly the same in the model and the data for each state. However, the model with only three parameters does not perfectly replicate the operational scale of each farm in the data. Nevertheless, the model closely replicates the efficiency gains in each state in the data (panel B).

We also provide information on the model fit of operational farm size and the share of operated land among the top 10 percent most productive farms in each state. Table 3, column (1), provides the correlation of farm size (in logs) between the model and the data. This correlation hovers around 80 percent for most states and is 85 percent for India. Columns (2) and (3) report the share of land operated by the 10 percent most productive farms in each state in the data and model. The model also captures well the differences across states in the allocation of land across the most productive farms, from Tamil Nadu where only 7 percent of the land is allocated to the most productive farms (8 percent in the model) to Punjab and Madhya Pradesh where 24 and 39 percent of the land is allocated to the most productive farms (26 and 28 percent in the model).

Table 3: Model Fit of Farm Operational Scales

	Correlation of operated land (log) model and data	Operated land share of 10% most productive	
		Data (2)	Model (3)
India	0.85	0.19	0.18
State:			
[AP] Andhra Pradesh	0.68	0.23	0.26
[AS] Assam	0.70	0.18	0.16
[BR] Bihar	0.73	0.19	0.21
[GJ] Gujarat	0.93	0.12	0.12
[HR] Haryana	0.73	0.19	0.17
[KA] Karnataka	0.91	0.12	0.12
[KL] Kerala	0.95	0.11	0.11
[MP] Madhya Pradesh	0.86	0.39	0.28
[MH] Maharashtra	0.94	0.17	0.16
[OR] Orissa	0.80	0.12	0.12
[PB] Punjab	0.77	0.24	0.26
[RJ] Rajasthan	0.85	0.13	0.15
[TN] Tamil Nadu	0.98	0.07	0.08
[UP] Uttar Pradesh	0.77	0.17	0.17
[WB] West Bengal	0.77	0.14	0.14

**Notes:** Column (1) reports the correlation between the share of land cultivated by farms in the data and the model in each state. Columns (2) and (3) report the share of land operated by the 10% most productive farms in each state in the data and the model. The model refers to the unweighted average of 100 simulations. Correlation for India is the raw correlation across all farms in India, and the land shares for India are sample means, weighed by total land per state.

## 4.2 Counterfactuals

Given the estimates of land-market distortions for each state, we now examine the role of state-level rental barriers  $\tau_s$  and idiosyncratic distortions  $\tau_{is}$  on agricultural productivity and other outcomes by conducting counterfactual experiments.

Starting from the baseline model in each state, we compute an “Efficient” counterfactual where we eliminate all land-market distortions, that is, we set  $\tau_s = 1$  and  $\tau_{is} = 0$  (i.e.,

$\theta_s = \sigma_{\epsilon s} = 0$ ), and recompute the equilibrium in each state. Table 4, column (1), reports the result of this counterfactual for agricultural TFP relative to the baseline model in each state. We also report the within state efficiency gain in India which is an output weighted average of the efficiency gain in all states. Note that while this experiment produces outcomes that are quite close to the reallocation gains in each state reported earlier, there are slight differences due to the fact that the baseline model is close but not identical to the actual allocations in each state. For instance, the within state efficiency gain for India is 1.63-fold in the data and 1.64-fold in the model.

Table 4: Counterfactual Agricultural TFP relative to the Baseline Model

	Efficient ( $\tau_s = 1, \tau_{is} = 0$ ) (1)	The role of idiosyncratic distortions (2)	state-level rental barriers (3)
India (within states)	1.64	1.27	1.29
State:			
[AP] Andhra Pradesh	1.51	1.34	1.12
[AS] Assam	1.79	1.68	1.06
[BR] Bihar	1.35	1.20	1.13
[GJ] Gujarat	1.97	1.45	1.36
[HR] Haryana	1.43	1.25	1.14
[KA] Karnataka	2.25	1.54	1.46
[KL] Kerala	1.98	1.49	1.33
[MP] Madhya Pradesh	1.44	1.17	1.23
[MH] Maharashtra	1.69	1.17	1.45
[OR] Orissa	1.72	1.49	1.16
[PB] Punjab	1.25	1.10	1.14
[RJ] Rajasthan	1.82	1.33	1.37
[TN] Tamil Nadu	2.64	1.10	2.39
[UP] Uttar Pradesh	1.36	1.18	1.15
[WB] West Bengal	1.24	1.10	1.13

**Notes:** Agricultural TFP relative to baseline model. “Efficient” refers to a counterfactual without distortions, when  $\theta_s = \sigma_{\epsilon s}^2 = 0$  and  $\tau_s = 1$ . The role of idiosyncratic distortions refers to a counterfactual with  $\tau_{is} = 0$  ( $\theta_s = \sigma_{\epsilon s}^2 = 0$ ). The role of state-level rental barriers refers to the contribution of  $\tau_s$  to efficiency gains in the “Efficient” counterfactual and is calculated as the ratio of column (1) to column (2). India (within states) refers to the output weighted average of efficiency gains in all states.

As discussed earlier eliminating all land distortions to achieve an efficient allocation of resources would produce a substantial increase in agricultural productivity, especially among the least productive states. An efficient reallocation of land within each state would increase agricultural productivity by 64 percent in India. But for some states the increase is much larger: 164, 125, and 98 percent in Tamil Nadu, Karnataka, and Kerala. We emphasize that such increases in TFP would have much larger effects on sectoral and aggregate productivity because of the additional effects that productivity growth has on the reallocation of labor out of agriculture (Restuccia et al., 2008; Adamopoulos and Restuccia, 2014), enhanced sectoral selection and investment (Adamopoulos et al., 2022; Bento and Restuccia, 2017, 2021), mechanization of agriculture and the adoption of other modern technologies (Chen, 2020; Ayerst, 2024), among others. Consistent with our previous finding, the productivity gains from an efficient reallocation of land across states are systematically related to rental market activity, with the largest TFP gains in states with the least active rental markets.

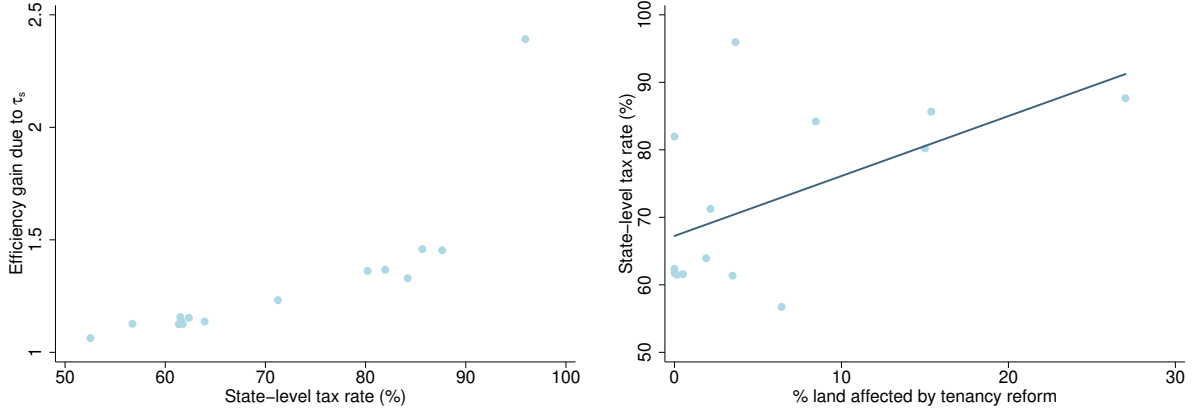
We now disentangle the contribution of state-level rental barriers  $\tau_s$  and idiosyncratic distortions  $\tau_{is}$  to efficiency gains in each state by computing an additional counterfactual where from the baseline model we eliminate idiosyncratic distortions, that is, we set  $\tau_{is} = 0$  for all farmers ( $\theta_s = \sigma_{\epsilon s}^2 = 0$ ). Note that in this counterfactual, state-level rental barriers  $\tau_s$  affecting land-market participation are still present, but some farmers may change their rental market participation decision based on the absence of idiosyncratic distortions. The result of this counterfactual, reported in Table 4 column (2), directly provides an assessment of the role of idiosyncratic distortions since it represents the productivity gains from the baseline model associated with the removal of idiosyncratic distortions. But this counterfactual also allows for the assessment of the contribution of state-level rental barriers  $\tau_s$  since removing rental barriers in this counterfactual renders the remaining productivity gains to the efficient level, the ratio of column (1) to column (2). In other words, we measure the contribution of state-level rental barriers to efficiency gains as the productivity gains generated by removing  $\tau_s$  from an economy without idiosyncratic distortions.

Our main finding is that state-level rental barriers  $\tau_s$  contribute substantially to depressing agricultural productivity. For instance, for the within-state reallocation in India, rental barriers contribute to an increase in agricultural TFP of 1.29-fold (a 29% increase), whereas idiosyncratic distortions contribute to an increase in agricultural TFP of 1.27-fold. As a result, state-level rental barriers  $\tau_s$  account for 51 percent ( $\ln(1.29)/\ln(1.64)$ ) of the efficiency gains associated with the within-state reallocation in India. In some states, such as Tamil Nadu, the contribution of rental barriers is even higher at 90 percent. Idiosyncratic distortions also contribute substantially to the increase in agricultural TFP, but the contribution of this type of distortions has already been highlighted in previous studies ([Adamopoulos et al., 2022](#); [Chen et al., 2022, 2023](#)).

We note that the contribution of state-level rental barriers  $\tau_s$  to efficiency gains in Table 4, column (3), is different from a counterfactual that removes rental barriers in the baseline model (setting  $\tau_s = 1$  in the baseline model). The reason for the difference is that we have assumed the same process for idiosyncratic distortions for rental market participants and non-participants, even though distortions are only directly measured for land market participants. In this setting with idiosyncratic distortions, the removal of  $\tau_s$  alone may or may not lead to a reallocation gain. Instead, we measure the contribution of  $\tau_s$  to efficiency gains by assessing the productivity gains from removing  $\tau_s$  in an economy without idiosyncratic distortions, which is given by the ratio of gains in column (1) to column (2). An alternative assumption would be that idiosyncratic distortions apply only to participants in the rental market. In this case, removing rental barriers  $\tau_s$  leads to rental participation and an efficient allocation of land for previous non-participants, rendering a larger contribution of rental barriers to efficiency gains than characterized in Table 4.

We note that efficiency gains associated rental barriers  $\tau_s$  are strongly linked to the calibrated value of  $\tau_s$ , as documented in Figure 11, panel A. As emphasized by [Restuccia and Rogerson \(2017\)](#), essential for policy implications is the connection of rental barriers  $\tau_s$  with specific institutional or policy features, an aspect that is beyond the scope of this article. Nevertheless,

Figure 11: Rental Barriers  $\tau_s$  and Agricultural Productivity Gains



**Notes:** State-level rental barriers  $\tau_s$  reported as a tax rate in percent,  $(1 - 1/\tau_s) \times 100$ . Productivity gains plotted are the contribution of state barriers to efficiency gains as reported in Table 4. Share of agricultural land affected by land reforms taken from [Kaushik and Haque \(2005\)](#).

we assess whether state-level rental barriers meaningfully capture differences in institutional quality across states. For this purpose, Figure 11, panel B, documents the measure from [Kaushik and Haque \(2005\)](#) reported earlier on the share of arable land transferred as a result of tenancy legislation across states, which proxies for rental market institutions; against our calibrated values of  $\tau_s$  across states. States with higher fractions of land affected by tenancy reforms have higher state-level rental barriers  $\tau_s$  in the calibrated model, indicating promise for future research decomposing the specific sources of rental barriers across states.

It is also instructive to illustrate the channels through which efficiency gains are attained in each state. Table 5 reports two statistics related to the extent of rental markets: the share of farms not participating in the land rental market and the share of cultivated land that is not rented. As discussed earlier, the baseline model implies large shares of farms not participating in the rental market and land not rented with important differences across states. The efficient counterfactual implies that all farmers would participate in the rental market and the share of land not rented would fall substantially, in India from 90 percent to 27 percent, with important differences across states. Most of these changes in the allocation of land, and hence the efficiency gains associated with them, are accrued due to the reduction



Table 5: Land Rental Activity by State

	Share of farms not participating in rental			Share of land not rented		
	Baseline	Efficient	$\tau_{is} = 0$	Baseline	Efficient	$\tau_{is} = 0$
India	0.75	0.00	0.64	0.90	0.27	0.83
State:						
[AP] Andhra Pradesh	0.70	0.00	0.44	0.86	0.33	0.72
[AS] Assam	0.72	0.00	0.34	0.91	0.23	0.51
[BR] Bihar	0.58	0.00	0.55	0.82	0.37	0.82
[GJ] Gujarat	0.92	0.00	0.62	0.98	0.18	0.78
[HR] Haryana	0.74	0.00	0.55	0.89	0.33	0.74
[KA] Karnataka	0.91	0.00	0.71	0.95	0.15	0.78
[KL] Kerala	0.92	0.00	0.65	0.97	0.22	0.77
[MP] Madhya Pradesh	0.77	0.00	0.69	0.87	0.31	0.89
[MH] Maharashtra	0.95	0.00	0.88	0.98	0.24	0.94
[OR] Orissa	0.72	0.00	0.49	0.92	0.18	0.62
[PB] Punjab	0.67	0.00	0.76	0.80	0.45	0.91
[RJ] Rajasthan	0.86	0.00	0.70	0.93	0.22	0.83
[TN] Tamil Nadu	0.98	0.00	0.88	0.97	0.10	0.98
[UP] Uttar Pradesh	0.65	0.00	0.63	0.83	0.35	0.84
[WB] West Bengal	0.67	0.00	0.62	0.91	0.40	0.87

**Notes:** “Efficient” is a counterfactual with no land distortions, i.e.,  $\tau_s = 1$  and  $\tau_{is} = 0$ , whereas  $\tau_{is} = 0$  is a counterfactual with no idiosyncratic distortions. The land shares for India are sample means, weighed by total land per state.

in rental barriers  $\tau_s$  since in the no idiosyncratic distortions counterfactual, the changes in the share of farms not participating and the amount of land not rented barely change or even increase.

## 5 Conclusions

We study land-market distortions and their impact on agricultural productivity across states in India. We develop a model of distorted land markets across heterogeneous farms that features state-level barriers to rental-market participation and idiosyncratic (farm-level) dis-

tortions to farm size. We use this framework to separately identify and estimate the two types of land-market distortions for each state. Our main finding is that there are substantial differences in barriers to rental-market activity across states with large negative effects on agricultural productivity. For instance, an efficient reallocation of land in India would increase agricultural TFP by 65 percent and by more than 100 percent in some states, with more than 50% of these effects attributed to state-level barriers to rental-market participation. Our findings suggest that land market distortions associated with rental market participation contribute substantially to agricultural productivity differences across states.

What are the specific institutional or policy features driving state-level rental barriers? Answering this question is essential for policy implications. Our description of the institutional environment in India has identified some possibilities for future research. First, we noted important differences across states in the quality of land records. Improvements in land records can reduce uncertainty and facilitate land transactions, leading to improved land and labor allocation and reduced misallocation ([Beg, 2021](#)). Improved land security can also reduce the legal backlog in land disputes. Third, legal reform to eliminate restrictions to land leasing (such as outright prohibition in some states or restrictions on lease duration and form of payment) can lead to increased land rental market participation and reduced misallocation.

Despite the importance of resource misallocation embedded in our results, there are substantial differences in agricultural productivity across states that remain unexplained. In our analysis, these differences are absorbed by state-level effects when measuring farm productivity. It would be of interest to investigate the role of other characteristics of agricultural production that may be associated with land market distortions across states. For instance, the adoption and diffusion of productive technologies (such as modern seed varieties, intermediate inputs, and mechanization) that are likely to depend on land distortions. Similarly, it remains relevant to study further the role of land quality differences in measured farm productivity. We leave these important areas of research for future work.

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# Online Appendix

## A Land Reforms in India

The key elements of land reforms were: (i) abolition of intermediaries, (ii) regulation of the size of land holdings (land ceiling legislation), and (iii) tenancy reforms to improve tenure security. Governments implemented the abolition of intermediaries quickly and successfully. Land ceiling legislation was often ineffective at transferring holdings to landless households. Authorities often set ceilings too high, as they exempted land that was “productively used”. Overall implementation was limited as state governments set additional costs and regulations. For example, [Jin et al. \(2006\)](#) describe how several states stipulated that beneficiaries of transferred land could only gain ownership rights once they had reimbursed the government for administrative expenses and the compensation it had paid to the original landowner. In Uttar Pradesh, beneficiaries did not receive ownership rights but became government tenants. In other states, new owners did not have the right to sell their new land for more than 10 years.<sup>3</sup>

Tenancy reform encountered considerable landlord resistance. [Deininger and Nagarajan \(2010\)](#) note that the implementation of land and tenancy reforms did not start in earnest until the 1970s. This allowed landlords to prepare by often evicting tenants and resuming self-cultivation, or by transforming tenants into wage workers. According to estimates by [Appu et al. \(1997\)](#) based on Census data, about 30 million tenants, one third of the total active population in agriculture, were evicted in order to avoid having to give rights to tenants.

Table [A.1](#) provides a summary of all land reforms passed between 1950 and 1980 from [Besley and Burgess \(2000\)](#). Table [A.2](#) summarizes each state’s restrictions on leasing land from [NITI Aayog, Govt. of India \(2016\)](#). The reforms show a variety of interventions across states, from providing tenure security and ownership rights to systems that limit lease rights. The main takeaway is that tenancy reform took many different forms across states.

Why did the legislation and implementation of land reforms differ so much across Indian states? In British India, land revenue systems differed markedly by state and district. For instance, in a landlord-based system, the landlord had effective property rights whereas in individual- or village-based system, property rights were diffused. [Banerjee and Iyer \(2005\)](#)

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<sup>3</sup>See also [Appu et al. \(1997\)](#) and [Mearns \(1999\)](#) for other anecdotal evidence suggesting that authorities implemented land ceiling reforms ineffectively.



Table A.1: Description of Land Reforms in Indian States

State	Year	Description
Andhra Pradesh (AP)	1954	Protected tenancy status, minimum lease term, right of purchase non-resumable land.
	1974	Tenancy $\leq 2/3$ ceiling, confers continuous right of resumption on landowners, tenant gets right of purchase.
Assam (AS)	1971	'Occupancy' tenants have tenure security and may acquire landholding, subletting disallowed.
Bihar (BR)	1957	Rights of permanent tenancy in homestead lands on persons with $< 1$ acre of land.
	1973	Prohibits subletting, prevents sub-lessees from acquiring occupancy rights.
	1986	Provides underraiyats possibility to acquire occupancy rights.
Gujarat (GJ)	1960	Tenants entitled to acquire ownership right after one year land expiry, dwelling sites.
	1973	Regulated, limited opportunity to acquire ownership rights for tenants.
Karnataka (KA)	1961	Grants tenants right to purchase, fixes tenure for $1/2$ leased area.
	1974	Removal of some exemptions earlier tenancy legislation.
Kerala (KL)	1963	Grants tenants right to purchase.
	1974	Call for employment security, fixed hours, minimum wages, etc..
	1979	Confers ownership rights on tenants with concealed tenancy.
Madhya Pradesh (MP)	1959	Past leasing prohibited, entitles tenants right to acquire.
Maharashtra (MH)	1950	Transfer of ownership to tenants of non-resumable lands (Marathwada region only).
	1958	Idem for all other regions
Orissa (OR)	1976	Tenure fixed for non-resumable area, subletting prohibited.
Punjab (PB)	1953	Tenure security for small-scale, continuous tenants.
	1955	Grants tenants right to acquire ownership of non-resumable land.
	1972	Limits on tenancy regulated land.
Rajasthan	1955	Confers tenure security to tenants and subtenants, ownership rights potentially transferable.
Tamil Nadu (TN)	1952	Greater tenure security.
	1956	Abolishment of usury and rack-renting.
	1965	Prohibition of tenant eviction.
	1969	Administration of tenancy records.
	1971	Prohibition of tenant eviction.
	1976	Acquisition rights for occupants.
Uttar Pradesh (UP)	1977	Tenants given complete tenure security, leases banned.
West Bengal (WB)	1950	Liberalization of sharecroppers harvest proportion.
	1953	Abolition of all intermediary tenures.
	1972	Full rights to tenants of homestead land.
	1975	Idem.
	1977	Raises presumption in favour of sharecroppers, minimum tenancy land size.

**Notes:** Land reforms from [Besley and Burgess \(2000\)](#). Year refers to most recent amendment. [Besley and Burgess \(2000\)](#) also include amendments when measuring the number of reforms.

argue that variation in these types of systems is mainly explained by date of British conquest. Most states that were conquered early had landlord-based system before conquest. As the landlord-based systems were easy to set up, but costly to change, these systems persisted into independence. After British elites experienced a shift in views on governance in the 1820s, it became easier to establish non-landlord systems in states that came under British control at a later stage. Independence fueled class-based resentment in states with landlord-based systems, which led to demands for land reforms (e.g., [Gough, 1974](#)).

Table A.2: Description of Tenancy Reforms in India

State	Law Governing Leasing	Nature of Legal Restrictions on Land Leasing
Andhra Pradesh	Andhra Pradesh (Andhra Area) Tenancy Act, 1956, as amended in 1974.	There is no explicit ban on leasing. But the terms and conditions of leasing are restrictive. Any lease after 1974 has to be in writing and registered, for a minimum period of six years. Also on resumption of land by the landowner, the tenant has to be left with not less than one half of the land held by him under lease prior to such resumption.
Telangana	The Andhra Pradesh (Telengana Area) Tenancy & Agriculture Act, 1950, as amended in 1951, 1954, 1956, 1961, 1969 and 1979.	Leasing is prohibited except for certain categories of land owners, such as (a) landowners who own land equal to or less than three times the family holding* (section-7) and (b) disabled persons (a minor, a female, persons with physical and mental infirmity, persons in defence services with permission of district collector). A copy of every lease shall be filed before the tehsildar.
Assam	Assam (Temporarily settled Areas) Tenancy Act, 1971, applicable to the entire state.	No explicit ban on land leasing. Sub-letting is prohibited. Occupancy tenants who have held land as tenant for at least three years continuously enjoy security of tenure and can acquire ownership right on payment of compensation at the rate of 50 times the rate of annual revenue, payable for such lands. Non-occupancy tenant can acquire the right of occupancy if he has held land continuously for three years.
Bihar	Bihar Land Reforms Act, 1961.	Leasing is prohibited except by disabled ryots, i.e. a minor, a widow, or an unmarried, divorced or separated woman, or a person with physical or mental disability, or a person in the armed forces, or a public servant in receipt of salary not exceeding Rs. 250 per month (Section 19).
Jharkhand	Chhotanagpur Tenancy Act, 1908 and Santhal Pargana Tenancy Act, 1945.	Leasing is prohibited, except with permission from a competent authority (the Deputy Commissioner). This is required not only for Adivasis, but also for Scheduled Caste or backward caste raiyats to lease out land. Besides, the land cannot be transferred even to an Adivasi who does not reside within the jurisdiction of the same police station to which the landowner belongs (Section 46(1) of CNTA).

*Continued on next page...*

Table A.2 — *Continued from previous page*

State	Law Governing Leasing	Nature of Legal Restrictions on Land Leasing
Gujarat	Bombay Tenancy And Agril, Land Act 1948, as amended by Act No. 5 of 1973 (erstwhile Bombay areas).	No explicit ban on land leasing, but the landowner risks losing the land when the tenancy is created. A tenant acquires the right to purchase the land leased within one year of lease period. Legal leases are possible only when the tenant is not in the position to exercise his or her right to purchase, due to financial difficulties or otherwise.
Gujarat	Saurashtra Land Reforms Act, 1951 and Prohibition of Leases Act, 1953.	Renewal of lease or a fresh lease after 1.9.1954 is prohibited except by persons under disability such as a widow, a minor, a member of the armed forces or persons suffering from physical or mental disability, or government, local authority, industrial and commercial undertakings.
Gujarat	Bombay Tenancy and Agricultural land (Vidharbha and Kutch Area) Act, 1958, as amended by Govt. of Gujarat in 1961, 1964, 1965, 1968 and 1973.	No explicit ban on land leasing. But the Act provides for voluntary purchase of ownership right.
Himachal Pradesh	The H.P. Tenancy and Land Reforms Act, 1972, as amended in 1976 and 1987.	Leasing out is banned except when done by disabled persons such as members of armed forces, unmarried, divorced or separated women, a widow, a minor, persons under physical or mental disability, or a student of a recognized institution.
Jammu & Kashmir	The Jammu & Kashmir Agrarian Reforms Act, 1976.	Creation of tenancy is banned without any exception.
Karnataka	The Mysore Land Reforms Act, 1961 as amended w.e.f. 1 March, 1974.	Leasing out is banned except when done by a soldier or a seaman.
Kerala	Kerala Land Reforms Act, 1963, as amended in 1969, 1971, 1972 and 1973.	Leasing out is banned without any exception.
Madhya Pradesh & Chhattisgarh	MP Land Revenue code, 1959, as amended up to date.	Leasing out is prohibited except when done by a disabled person (a widow, unmarried woman, married but separated woman, a minor, a person in imprisonment, a person serving in armed forces, a public charitable or religious institution, or a local authority, or a co-operative society).

*Continued on next page...*

Table A.2 — *Continued from previous page*

State	Law Governing Leasing	Nature of Legal Restrictions on Land Leasing
Maharashtra	Bombay Tenancy and Agricultural land Act, 1948, as amended in 1956 (for the old Bombay area) and The Hyderabad Tenancy and Agricultural Lands Act, 1950, as amended in 1954 for Marathwada (Hyderabad area).	No explicit legal ban on leasing. But the tenant has the right to purchase the land leased by him within one year of the creation of the tenancy. Any tenancy created after the tillers (i.e. 1st April, 1957) day, (except by the serving member of armed forces) is void, as the tenants shall acquire the right to purchase. Tenants cultivating personally on 1st April, 1957, i.e. the tillers day, shall be deemed to have purchased the ownership right from the landlord up to the ceiling area.
Odisha	Orissa Land Reforms Act, 1965, as amended in 1973 and 1976.	Leasing out agricultural land is banned except by a person under disability or under a privileged raiyat w.e.f. 1.10.1965. A person under disability includes: (i) a widow or unmarried or separated women (ii) a minor, (iii) a person incapable of cultivating land due to physical or mental disability, (iv) a serving member of armed forces, (v) a raiyat whose land holding does not exceed 3 standard acres. A privileged raiyat means Lord Jagannath, any trust or institution declared as a privileged raiyat, or any other religious or charitable trust of a public nature.
Manipur	The Manipur Land Revenue and Land Reforms Act, 1960 as amended in 1975 (applicable to plain areas only).	Leasing is banned except by a person with a disability.
Punjab	Punjab Tenancy Act, 1887, The PEPSU Tenancy and Agricultural Lands Act, 1955, as amended in 1957, 1959, 1962, 1968 and 1969; Punjab Security of Land Tenancy Act, 1953 as amended in 1955, 1957, 1959, 1962, 1968 and 1969 and Punjab Land Reforms Act, 1972.	No explicit ban on leasing. But section 16 of the LR Act, 1972 provides that the tenant of a big landowner is entitled to purchase his land if he has been in continuous possession of the land for a minimum period of six years, if the land is not included within the reserved or ceiling area of the landowner, or when the landowner is a disabled person (widow or unmarried woman, or a person suffering from physical or mental disability). The land of the tenant must be below the ceiling. the tenant must have land below ceiling. A landowner with land below the ceiling can evict a tenant, subject to the tenant being left with not less than five standard acres.
Haryana	Punjab Security of Land Tenures Act, 1953 for the erstwhile Punjab area and PEPSU Tenancy and Agricultural Land Act, 1955 for PEPSU area, as amended up to date.	No explicit ban on land leasing. But there are other restrictive clauses, as in Punjab. However, the Haryana law does not provide the right to purchase rented land land falling within the ceiling surplus areas of land owner, as in Punjab. Such land vests in the government, although tenants are given preference in the allotment of such lands. A tenant can lease in land for a minimum period of three years, and a maximum of six years.

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Table A.2 — *Continued from previous page*

State	Law Governing Leasing	Nature of Legal Restrictions on Land Leasing
Rajasthan	Rajasthan Tenancy Act, 1955.	There is no explicit ban on land leasing. But the terms and conditions of lease are restrictive. A tenant is entitled to a written lease, which may be attested if not registered.
Tamil Nadu	Madras cultivating tenants protection Act, 1955 as amended in 1965 and Madras cultivating Tenants (payment of Fair rent) Act, 1956.	There is no explicit ban on leasing. But the landlord can use the land for personal cultivation, not exceeding one half of the land leased out to the tenant except when he is a member of armed forces. If the landlord owns above 13.5 acres of wet land, or pays sales, professional, or income tax, he cannot even resume land from the tenant. A tenant or agricultural laborer occupying any Kudiyrupes (a dwelling house or hut) cannot be evicted.
Tripura	The Tripura Land Revenue and Land Reforms Act, 1960.	A raiyat or jotedar can lease out, but the tenant can hold the land in perpetuity. The lease cannot be terminated except by a person with a disability, i.e. a widow, a minor, an unmarried woman, or a divorced or judicially separated woman, or a member of the armed forces, or a person under physical or mental disability. A tenant under raiyat cannot be evicted from his land except by an order of a competent authority on specific grounds.
Uttar Pradesh & Uttarakhand	The Uttar Pradesh Zamindari Abolition Land Reforms Act, 1950.	Leasing is banned except when done by a disabled person and to agriculture-related educational institutions. A disabled person is defined as an unmarried, divorced, or separated woman, a widow, or a woman whose husband is incapable of cultivating due to physical or mental infirmity, or a minor whose father suffers from infirmity, or a person who is a lunatic or an idiot or blind, or a student of a recognized educational institution whose age does not exceed 25 years and whose father suffers from infirmity, or a serving member of the armed forces, or a person under detention or imprisonment.
West Bengal	The West Bengal Land Reforms Act, 1955 as amended in 1970, 1971 and 1981.	Only sharecropping is allowed. No fixed rent or fixed produce tenancy is allowed, not even by a person with a disability of any kind.

**Notes:** Source [NITI Aayog, Govt. of India \(2016\)](#).

## B Data

We describe more details of data, constructed variables, and sample selection. We also provide details of expenditure measures used for the production function parameter estimates.

## B.1 Variables and Sample Selection

**Real gross output.** A natural measure of real output at the farm level is crop output aggregated using constant crop prices across farms and time. However, only wave I of IHDS reports crop-level output. We first calculate nominal farm revenue by aggregating up crop level revenue using farm-level prices reported in wave I. While wave II of IHDS does not report the crop-level output information for farms, it however provides the total nominal revenue calculated by using the crop quantities and price information that is not publicly available in the IHDS database. Because we lack data on price deflators for agriculture by state, we use food CPI for agricultural workers in each state from the Indian Ministry of Labour and Employment. We express constant prices over time relative to wave I and across states relative to Punjab. We corroborate that our revenue measure of output correlates strongly with the real measure of output from wave I using common prices for crops, with a mean correlation across states of 78 percent.

**Land.** Wave I reports total land owned, own land cultivated, land rented-in, and land rented-out by the farmer in the last 12 months. Wave II reports total land owned, land rented-in, and land rented-out by farmer in each of the three main cropping seasons in India - kharif, rabi, and summer. We measure total land cultivated as the sum of own land cultivated and land rented-in in wave I. In wave II, we calculate total land cultivated (own land + rented-in - rented-out) by season and then take the maximum value of the three. Similarly, total land rented-in and rented-out are taken as the maximum over all three seasons reported.

**Labor.** Both waves report details on hired and household labor. Hired labor is reported in total mandays hired in the last 12 months. Household labor is reported in terms of the average number of hours and the average number of days a year each member of the household worked on the farm. We calculate total number of hours of labor provided by the

household and use a value of 8 hours per manday to convert to total mandays. We do not include the labor provided by the farm head, household head, or their spouse in total labor as we believe they capture managerial inputs for the farm and should be captured in farm productivity. The IHDS village data file provides average agriculture wages paid to men, women, and children separately. We adjust household labor by deflating the hours worked by women and children using the relative median wages paid to them from the village data file.

**Capital.** The stock of capital is calculated as the value of electric pumps, diesel pumps, bullock carts, tractors, threshers, and draft animals owned by the farm. We impute the value of machinery using 1997-98 prices reported in table 24 of [Singh \(2006\)](#). Electric and diesel pumps are priced at Rs. 18,000, bullock carts at Rs. 10,000, tractors at Rs. 250,000, and threshers at Rs. 25,000. For draft animals, we first take the average value of the minimum and maximum reported price for draft animals in the village database of the respective wave of IHDS, and then use the median of this value. A measure of capital stock owned is then constructed as the total value of all machinery and draft animals owned by the farm.

IHDS also reports expenditure on renting capital as well as income made from renting out capital from the farm. We convert these rental values to capital stock values by deflating with a measure of real interest rate in each wave. We use the median nominal interest rate paid by households on loans from banks (reported in the household data file of the IHDS) and adjust it using the inflation rate for the corresponding year to convert to real terms. Total capital stock employed on the farm is calculated as capital owned plus capital rented in minus any capital rented out. To this value we finally add a minimum amount of capital to every household equal to 10 percent of the median capital-to-land ratio multiplied by operated land to account for basic tools used on the farm not usually reported in the data.

**Materials.** We use the sum of expenditure on seeds, fertilizers, pesticides, and other miscellaneous expenses and deflate it using the price of kerosene that the household pays as the amount of materials used on the farm. While the level of kerosene prices may differ from that of other intermediate inputs (e.g. fertilizer), our empirical approach requires only that we identify relative farm TFP within each state. We believe kerosene prices are a good proxy since they reflect the same relative trade costs that drive relative intermediate input prices. For those households that report zero spending on material inputs, we impute material expenditure as the minimum value of material-to-land ratio multiplied by operated land.

**Final sample.** We start by dropping all households who report no cultivated land or zero agriculture output in each wave. Of the 14,738 households participating in agriculture in wave-I, we match 10,253 to wave-II to create a balanced panel. The rest of the households are dropped either because they leave farming, split up households, or are lost to re-contact. After restricting our analysis to states with an estimated population of more than 20 million, we are left with a sample of 8,147 households in 15 states for the analysis. The states in our final sample are: Andhra Pradesh (AP), Assam (AS), Bihar (BR), Gujarat (GJ), Haryana (HR), Karnataka (KA), Kerala (KL), Madhya Pradesh (MP), Maharashtra (MH), Orissa (OR), Punjab (PB), Rajasthan (RJ), Tamil Nadu (TN), Uttar Pradesh (UP), and West Bengal (WB). These states account for 97% of India’s population and 92% of value added in agriculture in 2011.

Once we estimate the permanent component of TFP, we trim our sample by dropping the top and bottom 1% of the TFP distribution by state. Finally, we exclude households that experience large changes in land-to-output ratios between the two waves. This leaves us with 7,846 households across 15 states. We use sample weights provided in the dataset to expand the dataset for all quantitative exercises.



## B.2 Production Function and Productivity

**Production function parameters.** In order to measure farm productivity, recall that we assume a common production function that only differs across farmers in terms of their total factor productivity given by equation (1). We use aggregate expenditure shares of revenue of factor inputs for all farms in the data to calibrate each input elasticity following the literature that uses factor cost shares to estimate production functions (Syverson, 2004; Raval, 2023). This approach is common in the macroeconomics literature Valentinyi and Herrendorf (2008) and in particular a recent literature on agriculture (Adamopoulos and Restuccia, 2014; Chen et al., 2023). Under the assumptions that farms are price takers and minimize costs, and that static first order condition for each input holds on average in the market, we can map each factor’s expenditure relative to total farm revenue to its output elasticity in the production function.

To measure factor shares, we convert input quantities to input expenditures using common prices for all farms in India. For land, we use the rental price paid by farms renting-in land. These rents can be paid either in cash, as a share of crop, or both. We back out a measure of the rental price of land by using the median price paid by farmers per unit of land rented-in by cash only in each wave respectively. Land expenditure is calculated as the product of total operated land and the median rental price.

For labor, we use the median wage rate paid for hired labor (using only those households that do not provide meals to hired labor) to obtain a measure of expenditure on hired labor. Expenditure spent on household labor is constructed as the product of the adjusted household labor with the median agriculture wage paid to men from the village data file. Total labor expenditure is the sum of expenditure on hired and household labor.

We convert the constructed capital stock value into expenditure terms by multiplying it with the rental rate of capital for each wave (described above in the variables description). Materials are converted into expenditure terms using a common price set as the median price

of kerosene in the dataset.

Table B.3 reports the factor shares for capital, land, labor, and materials using data from IHDS-I and the implied production function parameter values. The resulting parameter estimates are broadly consistent with estimates from other studies (Adamopoulos et al., 2022; Aragón et al., 2022; Chen et al., 2022).

Table B.3: Factor Input Shares and Production Function Parameters

Input factor	Output elasticity	Data	Parameter	Value
Capital	$\alpha(1 - \theta)\gamma$	0.11	$\alpha$	0.20
Land	$\beta(1 - \theta)\gamma$	0.25	$\beta$	0.43
Labor	$(1 - \alpha - \beta)(1 - \theta)\gamma$	0.19	$\theta$	0.28
Materials	$\theta\gamma$	0.20	$\gamma$	0.75

**Notes:** Data from IHDS wave I 2004-05 (Desai et al., 2005). Factor shares are calculated as the ratio of input expenditure across farms in India to the value of total farm output.

**Crop-level production.** Note that while our data reports crop-level output for wave I, we do not have information on inputs used by crop within the farm required to estimate crop-level productivity. Moreover, crop-level information is not reported in wave II which would prevent us from estimating the permanent component of farm productivity. However, we examine potential differences in factor shares across crops. We classify farm households that generate more than 50 percent of their estimated revenue from a single crop and restrict to crops that are produced by at least 100 farm households in the wave I sample. Estimating factor shares as described previously, we find that factor shares are roughly similar across crops and in line to the baseline values used in our calibration.

To allay concerns that crop differences in factor shares can substantially affect our farm productivity estimates, we back out production function residuals  $\ln a_{ist}$  using crop-specific input shares and compare them to our baseline production function residuals. We find that

the two measures of farm productivity (in logs) are strongly correlated across farms within states with West Bengal having the smallest correlation coefficient of 0.86 and Assam having the highest correlation at 0.97, and the average correlation coefficient across states being 0.93.

**Land as composite input.** Our analysis focuses on a production function with land as a composite input. This implies that we abstract from any variation in input ratios across farms and, as a result, is conservative in the quantification of reallocation gains. We write the production function defined in equation (1) in the main text in terms of input ratios and land (with state and time subscripts dropped for ease of exposition):

$$y_i = z_i \underbrace{\left[ ((k_i/\ell_i)^\alpha (n_i/\ell_i)^{1-\alpha-\beta})^{1-\theta} (m_i/\ell_i)^\theta \right]^\gamma}_{\text{Input ratios: } T_i} \ell_i^\gamma \quad (\text{B.1})$$

To the extent that the variation in input ratios may be due to technology differences across farmers (the type of technology they use or the type of crops they grow), we abstract from this source of variation in our analysis. As discussed in the institutional context, legal rights to land is an essential requirement for farmers in India to access institutional credit and other farm benefits. Frictions to accessing land would then show up as frictions on other factors of production as well. Nevertheless, we emphasize that in measuring farm-level total factor productivity in the data, we do control for all factor inputs in addition to land.

We also note that in our data, the variation in input ratios across farms accounts for less than 14% of the variation in output. Taking the logarithm of equation (B.1), we have

$$\ln(y_i) = \ln(z_i) + \ln(T_i) + \gamma \ln(\ell_i), \quad (\text{B.2})$$

where  $T_i$  represents the component of the production function that captures variation in input ratios across farms.

Table B.4: Variance Decomposition of Production Function

	(1) $\ln(z_i)$	(2) $\ln(T_i)$	(3) $\gamma \ln(\ell_i)$
$\ln(y_i)$	0.366*** (0.005)	0.137*** (0.005)	0.497*** (0.005)
Observations	7,846	7,846	7,846
R-squared	0.453	0.094	0.527

**Notes:** Standard errors in parentheses. Each column regresses a component of the production function in equation (B.2) on the log of output, including a constant. The estimate represents the fraction of the variance in the log of output explained by the variance in the respective component of the production function. The coefficients in each column sum to 1. \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

Table B.4 reports the regression coefficients from regressing each of the components on the right hand side of equation (B.2) on the log of output separately. Each of the coefficients represent the fraction of the variance in the log of output explained by the variation in the corresponding factor, which all sum to one. We find that while the composite land input accounts for around 49.7% of the variation in output, the component made up of the other input ratios,  $T_i$ , captures only 13.7%.

## C Efficient Allocations and Gains.

Since our analysis focuses on land as a composite input, we measure farm output in the data based on our estimates of farm productivity  $z_{is}$  and operated land  $\ell_{is}$  for all farms and states in our data using the production function  $y_{is} = z_{is} \ell_{is}^\gamma$ . Then aggregate agricultural output is the sum of farm output in each state.

A useful benchmark for comparing allocations and aggregate outcomes is the efficient allocation, i.e., the allocation that maximizes aggregate output in a state given aggregate inputs. We characterize each state efficient allocation by solving the farm-level allocation of land

that maximizes aggregate output subject to the state's endowment of land  $L_s$ :

$$\max_{\{\ell_{is} \geq 0\}_{i=1}^{F_s}} \sum_{i=1}^{F_s} z_{is} \ell_{is}^\gamma, \quad \text{subject to} \quad \sum_{i=1}^{F_s} \ell_{is} = L_s.$$

The efficient allocation with superscript  $e$  involves allocating factors across the given set of  $F_s$  farmers in state  $s$  according to their relative productivity given by:

$$\ell_{is}^e = \frac{z_{is}^{\frac{1}{1-\gamma}}}{\sum_{i=1}^{F_s} z_{is}^{\frac{1}{1-\gamma}}} L_s.$$

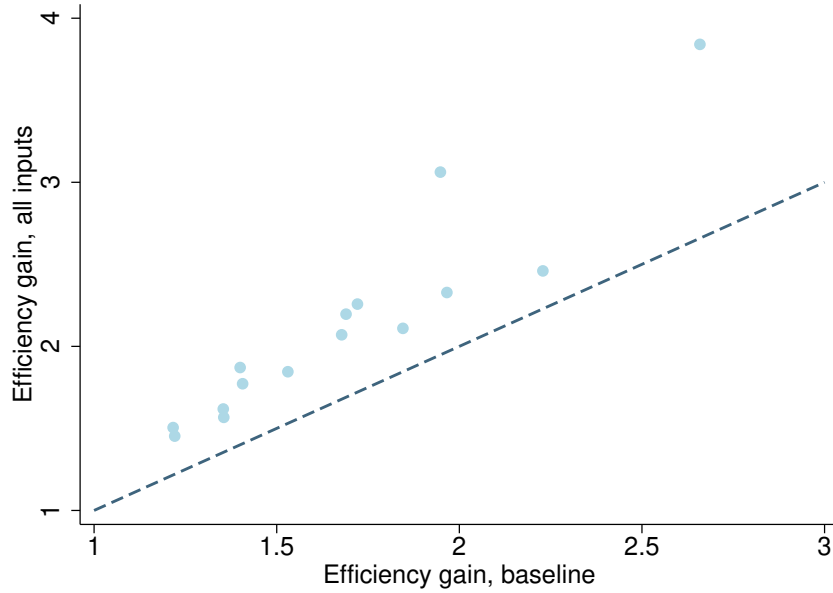
It is straightforward to show that aggregate output in the efficient allocation,  $Y_s^e$ , is a Cobb-Douglas aggregate of total inputs (land and total number of farms), and agricultural TFP  $A_s^e$ , see [Adamopoulos et al. \(2022\)](#) for a derivation and extension with more inputs:

$$Y_s^e = A_s^e F_s^{1-\gamma} L_s^\gamma, \quad \text{where} \quad A_s^e = \left[ \frac{1}{F_s} \sum_{i=1}^{F_s} z_{is}^{\frac{1}{1-\gamma}} \right]^{1-\gamma}.$$

We define efficiency gain as the ratio of aggregate efficient output to aggregate actual output in the data for each state,  $Y_s^e/Y_s^a$  ([Hsieh and Klenow, 2009](#)).

**Efficiency gains with all inputs.** While our empirical estimates of farm productivity take into account all inputs, in our analysis of reallocation gains we abstract from variation in input ratios across farms. This abstraction is conservative on the magnitude of reallocation gains since input ratios may also be distorted across farms. We make this abstraction because part of this variation may be due to technology differences across farms that we are not able to control for as well as differences across farms in the composition of crop production. Nevertheless, we illustrate the quantitative importance of variation in input ratios across farms in each state in our sample in [Figure C.1](#). The x-axis displays our baseline efficiency gains with land input reallocation, whereas the y-axis displays efficiency gains with all inputs. The dashed line is the 45 degree line representing equal efficiency gains in both measures.

Figure C.1: Efficiency Gains across States



**Notes:** Efficiency gains in each state with all inputs and with land input (baseline). Data from IHDS wave II 2011-12 (Desai et al., 2012).

As expected, efficiency gains are larger when all inputs are reallocated, but the two measures of efficiency gains are highly correlated (a correlation coefficient in logs of 94%) and the average efficiency gains with land input represent 69% ( $\log(1.68)/\log(2.13)$ ) of the average overall gains with all inputs. This result echos similar findings for the agricultural sector in other contexts (Adamopoulos et al., 2022; Chen et al., 2023) and the limited relevance of capital-to-labor ratio differences across manufacturing plants in China, India, and the United States documented in Hsieh and Klenow (2009).

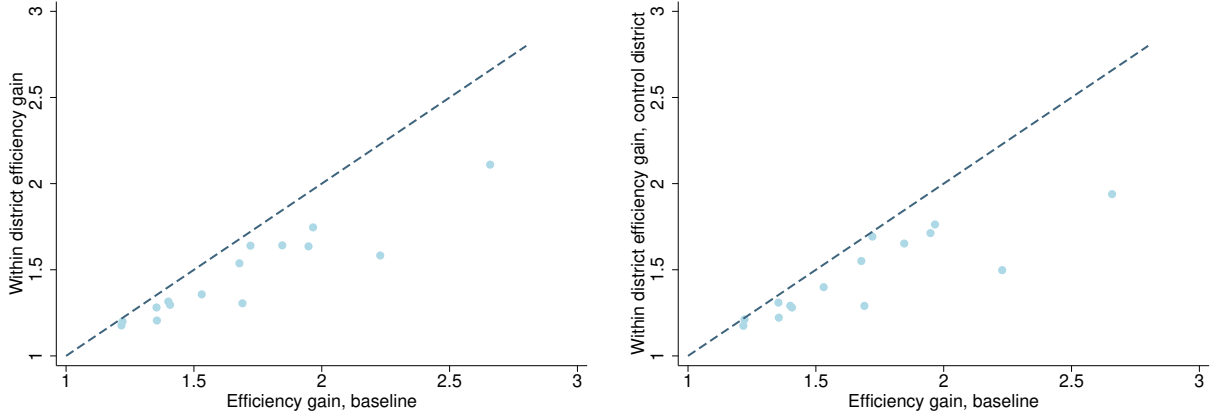
**Efficiency gains within districts.** A potential concern with our farm-level productivity measure is that it does not control for land quality differences. Unfortunately, our dataset does not have land quality measures at the farm and sub-region levels. We address this issue in two ways. First, we discuss evidence in other contexts where land quality differences are found to be a small portion of overall differences in farm productivity. For instance, Chen

et al. (2023) analyze detailed micro data for Malawi with land quality dimensions at the plot level. They document an expected pattern that land quality differences are larger across geographical dispersed areas with land quality variation dropping by half from the region level to the district level. Similar finding in less granular data is found in Adamopoulos and Restuccia (2022). Moreover, Adamopoulos et al. (2022) and Adamopoulos and Restuccia (2020) find that variation in land quality across villages account for a small portion (around 1 to 2%) of the variation in farm productivity in China and the Philippines.

Second, motivated by the evidence of larger differences in land quality across more dispersed geographical areas, we provide measures of efficiency gains that restrict reallocation to the district level within a state. For each district in a state and using our baseline measures of farm productivity that adjust for state-level effects, we compute the efficient allocation of land and the corresponding agricultural output, and then aggregate these outputs for all districts in a state. Efficiency gains within districts is just the aggregate efficient output in all districts in a state relative to actual aggregate output in the state. This measure is equivalent to an output weighted measure of district efficiency gains in a state and we refer to this measure as simply within district efficiency gain in each state. Figure C.2, panel A, documents the efficiency gain within districts against our baseline measure of efficiency gains for each state. The efficiency gains are strongly correlated (correlation coefficient in logs of 0.93) and in average the within district efficiency gains represent 74% ( $\log(1.468)/\log(1.68)$ ) of the average baseline efficiency gains.

In addition, we also conduct an alternative measurement of farm productivity that adjusts for district-level effects as opposed to state-level effects as in our baseline measure. The idea with this alternative estimate is that the farm TFP residual at the district level removes potential variation in land quality across districts within a state. Note of course that district-level effects may be removing real productivity variation across districts that is not related to land quality and as a result the alternative estimates are an upper bound of the importance of land quality differences across districts. We use the individual fixed-effect from equation

Figure C.2: Efficiency Gains within Districts in each State



**Notes:** Efficiency gains of within district reallocation when farm productivity controls for state-level effects and district-level effects. Data from IHDS wave II 2011-12 (Desai et al., 2012).

(2),  $\ln a_{is}$ , where  $s$  indexes the state that farmer  $i$  belongs to. Since we have information on the district  $d$  that farmer  $i$  belongs to, in the second step, we remove from the individual farm fixed effect the district level instead of the state level by running a regression as follows with district dummies:

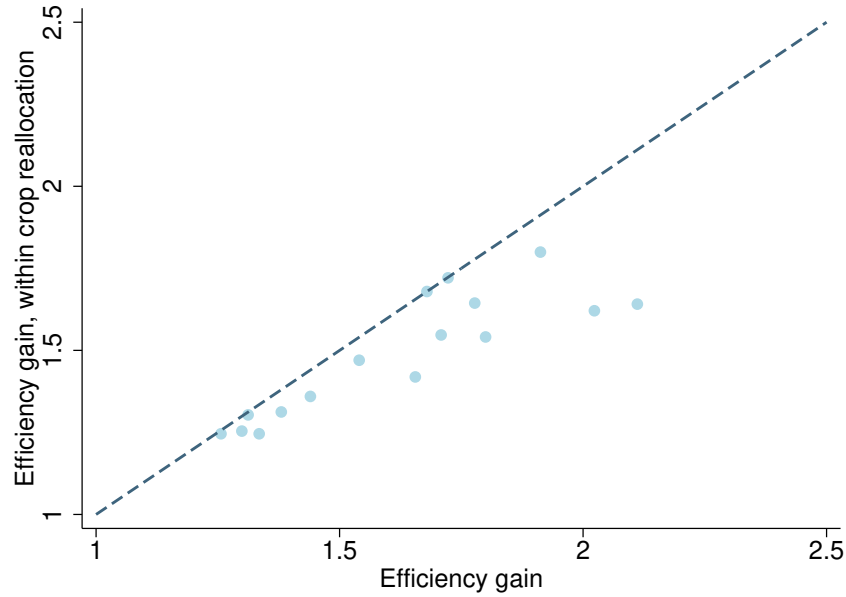
$$\ln a_{is} = \ln a_d + \ln z_{id}. \quad (\text{C.3})$$

We use the residual  $\ln z_{id}$  from the above specification as an alternative measure of farm TFP that excludes district-level productivity differences inclusive of land quality effects within a state. As in the previous analysis, we also only reallocate land efficiently within a district in a state and report the within district efficiency gain in this measure.

Figure C.2, panel B, plots efficiency gains in each state using our baseline measure of farm TFP  $z_{is}$  against the alternative measure of farm TFP  $z_{id}$  that controls for district and time fixed effects and hence controls for potential differences in land quality across districts. The results are consistent with our previous findings in that efficiency gains are strongly correlated (correlation coefficient of 0.88) and in average the within district efficiency gains represent



Figure C.3: Efficiency Gains within Crops in each State



**Notes:** Efficiency gains when reallocation is only within a crop in a state against the baseline efficiency gains in each state (same sample). Data from IHDS wave I 2004-05 ([Desai et al., 2005](#)).

74% ( $\log(1.465)/\log(1.68)$ ) of the average baseline efficiency gains.

**Robustness on within crop reallocation.** We evaluate the robustness of efficiency gains when reallocation is restricted to farms with similar crop production in a state. Since crop-level output data is available only for wave I, we restrict this analysis to the wave I (2004-05) instead of wave II (2011-12) as in the baseline. Our baseline efficiency gains are recalculated for the wave I data.

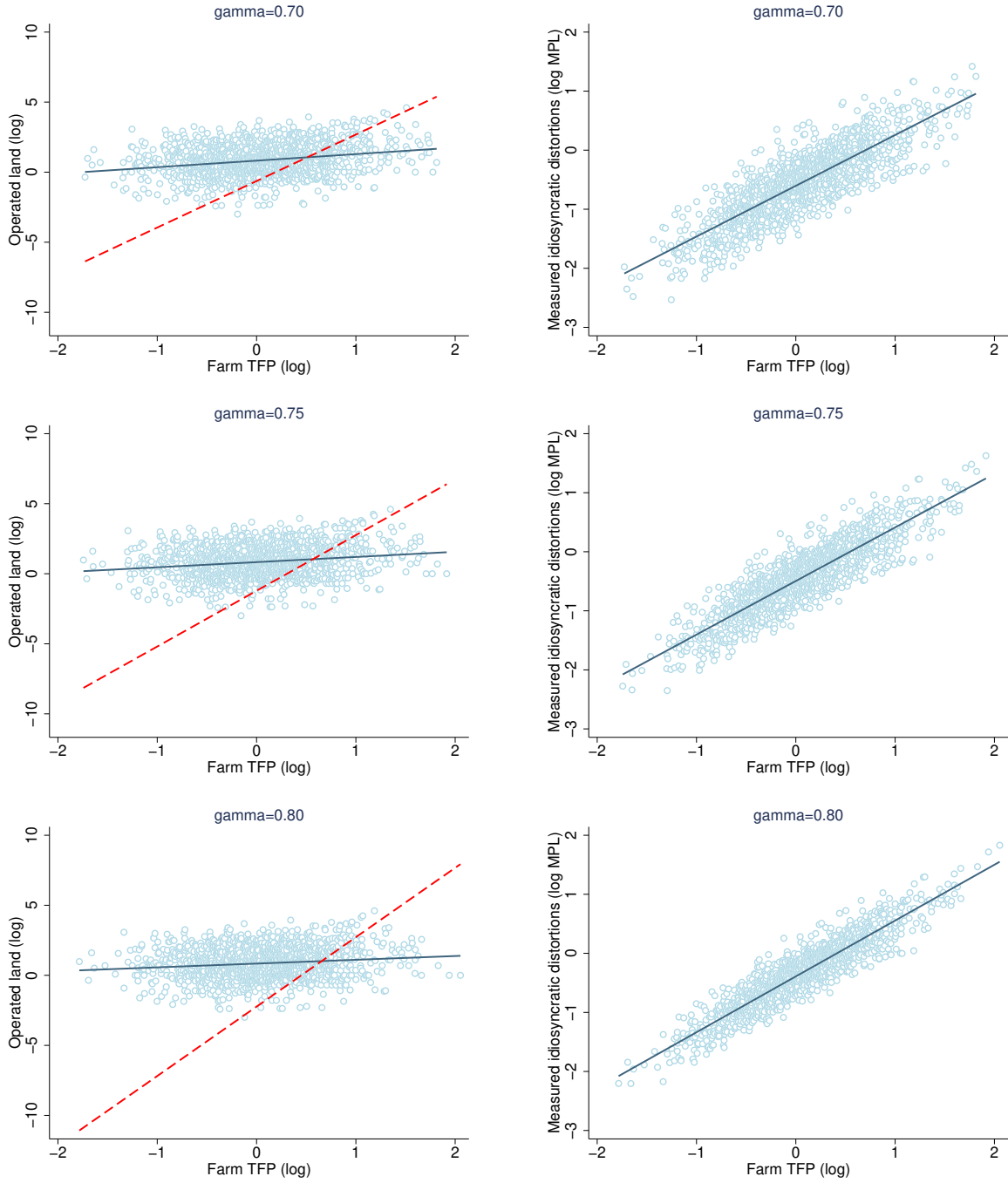
To characterize within crop reallocation, we first classify farms as producing a crop if more than half their estimated revenue is generated by one crop. From this set, we then restrict only the crops which are being produced by at least 10 households in a state in the (unweighted) sample. This leads to 29% of household level observations being dropped from the final sample. Note that the crop selection procedure results in states having different sets of crops. For example, Assam has only one crop that is produced by at least 10 house-

holds, while Karnataka has 14 different crops. We then expand our data using the household weights to carry out the reallocation exercises. In each state and for each crop, we compute the efficient allocation of land across farms within a crop. We then aggregate these gains at the state level to represent the within crop efficiency gain in each state. Figure C.3 documents the within crop efficiency gain against the baseline efficiency gain in a state. We find that these alternative measures of reallocation gains are strongly correlated (correlation coefficient in logs of 0.90) and that the within crop efficiency gains represent 82% ( $\log(1.488)/\log(1.62)$ ) of the average baseline efficiency gains.

**Robustness with respect to  $\gamma$ .** We evaluate the robustness of farm-level TFP and misallocation measures on the value of decreasing returns to scale parameter  $\gamma$ . We consider two alternative values of  $\gamma$  from the baseline 0.75 to 0.70 and 0.80. For each value of  $\gamma$ , we recalculate farm-level TFP, distortions, and misallocation measures. We find that our measures of farm-level TFP are not too sensitive to reasonable values of  $\gamma$ , for instance for India the standard deviation of log TFP is 0.626 with baseline  $\gamma = 0.75$  and changes to 0.638 with  $\gamma = 0.70$  and 0.617 with  $\gamma = 0.80$ . The reason for this result is that land varies much less across farms than the variation in output, and our fixed effect procedure eliminates level differences. As a result of this, and the fact that land input is given by data, the elasticity of land with respect to farm TFP is relatively unaffected by changes in  $\gamma$  as documented in Figure C.4 for farmers that participate in the land rental market.

Changes in  $\gamma$  have a larger impact on the efficient allocations given a distribution of TFP since higher  $\gamma$  would require more reallocation of inputs to productive farms to equalize marginal products. But the differences in standard measures of misallocation are relatively small as documented in Figure C.4. For example, the elasticity of distortions with respect to farm TFP changes from 0.91 in the baseline  $\gamma = 0.75$  to 0.87 with  $\gamma = 0.70$  and 0.94 with  $\gamma = 0.80$ . These changes are small when compared to the elasticity implied in the efficient allocation of 3.3 with  $\gamma = 0.70$  and 5 with  $\gamma = 0.80$ .

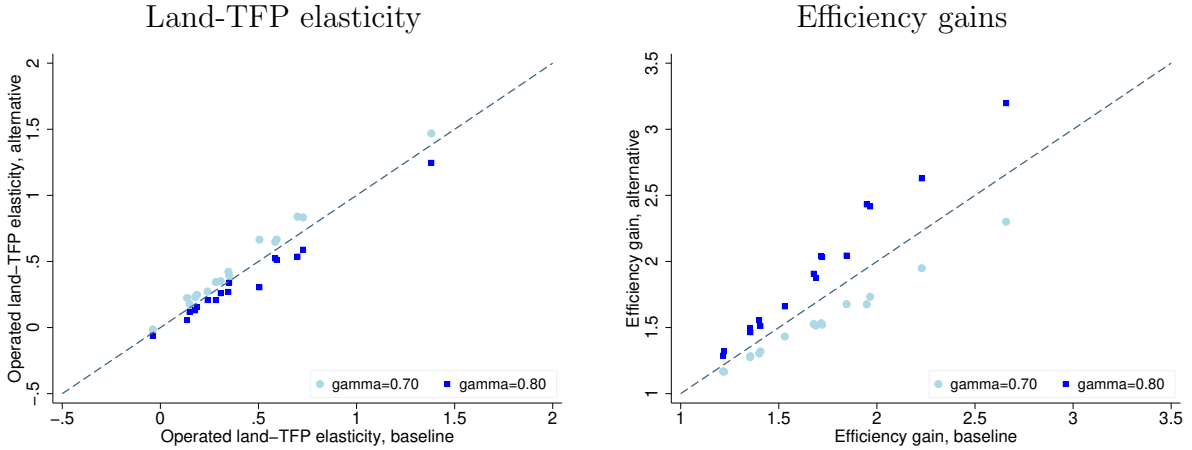
Figure C.4: Land, Distortions, and Productivity



**Notes:** The first-column figures report the relationship between farm land and TFP for farmers participating in the land market in India for alternative values of  $\gamma$ , where  $\gamma = 0.75$  is our baseline calibration. The red dashed line is the efficient slope for reference. The second-column figures report the relationship between measured farm distortions and TFP. The solid line is the best fit. Data from IHDS wave I 2004-05 ([Desai et al., 2005](#)).

More importantly, our analysis emphasizes differences across Indian states and while changes in the production function can affect the level in measures of misallocation, ranking differences across states are robust to variation in  $\gamma$ . Figure C.5 reports changes in measures of misallocation in each state for the alternative values of  $\gamma$ . We also note that efficiency gains are not necessarily monotone with respect to changes in  $\gamma$  since as reported previously  $\gamma$  has opposing effects on the variance of TFP and efficient allocations, see [Hopenhayn \(2014\)](#) for a broader discussion of this point.

Figure C.5: Misallocation Measures and  $\gamma$



**Notes:** Panel A reports the land-TFP elasticity across farms in each state and Panel B reports efficiency gains in each state. The x-axis represents the value in the baseline  $\gamma = 0.75$  case, whereas the y-axis represents the alternative values ( $\gamma = 0.70$  in circles and  $\gamma = 0.80$  in squares).

## D Model Details

We provide details of the algorithm used to solve the competitive equilibrium, the procedure to calibrate land distortions to data moments for each state, and other results of the quantitative analysis.

## D.1 Solving for the Competitive Equilibrium

Each state is characterized by the number of farms  $F_s$ , total cultivated land  $L_s$  in IHDS-II, and farm-level productivity and land endowment  $\{z_{is}, \bar{\ell}_{is}\}$  for each farmer in the state.<sup>4</sup> We use the following algorithm to solve for the competitive equilibrium in each state given distortions parameters  $\theta_s$ ,  $\tau_s$ , and  $\sigma_{\epsilon s}$ :

1. For each farm, draw  $\epsilon_{is} \sim N(0, \sigma_{\epsilon s}^2)$ .
2. Compute the marginal product of land at the endowment  $MPL_{\bar{\ell}_{is}} = \gamma z_{is} \bar{\ell}_{is}^{\gamma-1}$ .
3. Guess land price  $q_s$  (as initial guess we use the land price associated with the efficient allocation) and compute:
  - $\ln q_{is}^{in} = \ln q_s + \theta_s \ln z_{is} + \epsilon_{is}$ ,
  - $\ln q_{is}^{out} = \ln q_s + \theta_s \ln z_{is} + \epsilon_{is} - \ln \tau_s$ .
4. Partition farms into three sets and compute land demand  $\ell_{is}$  for each farm:
  - $\ell_{is} = \left( \frac{\gamma z_{is}}{q_{is}^{in}} \right)^{\frac{1}{1-\gamma}}$ , if  $\ln MPL_{\bar{\ell}_{is}} > \ln q_{is}^{in}$ ,
  - $\ell_{is} = \left( \frac{\gamma z_{is}}{q_{is}^{out}} \right)^{\frac{1}{1-\gamma}}$ , if  $\ln MPL_{\bar{\ell}_{is}} < \ln q_{is}^{out}$ ,
  - $\ell_{is} = \bar{\ell}_{is}$ , if  $q_{is}^{in} \geq \ln MPL_{\bar{\ell}_{is}} \geq \ln q_{is}^{out}$ .
5. Compute relative excess land demand as  $f = \frac{\sum_{i=1}^{F_s} \ell_{is}}{L_s} - 1$ .
6. If  $abs(f) < tol$ , done. Otherwise, adjust  $q_s$  and repeat steps 3 to 6 until convergence.

## D.2 Estimation of Land Distortions

We describe the details of the procedure we follow for estimating the parameters of land market distortions  $\tau_s$ ,  $\theta_s$ , and  $\sigma_{\epsilon s}$  in each state.

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<sup>4</sup>We adjust land endowment as a proportion of total cultivated land in each state.

**Targeted moments.** We use three sources of variation in the data to identify the three parameters determining land distortions:

- If  $\tau_s = 1$ , all farmers participate in the land rental market, hence the share of farmers not participating in the land rental market provides variation to identify  $\tau_s$ .
- If  $\tau_s = 1$  and  $\theta_s = 0$ , the covariance between  $\ln MPL_{is}$  and  $\ln z_{is}$  equals zero, hence this covariance provides variation to identify  $\theta_s$ , conditional on  $\tau_s$ .
- If  $\tau_s = 1$ ,  $\theta_s = 0$ , and  $\sigma_{\epsilon s} = 0$ , the variance of  $\ln MPL_{is}$  equals zero, hence this variance provides variation to identify  $\sigma_{\epsilon s}$ , conditional on  $\tau_s$  and  $\theta_s$ .

Given our estimates of farm productivity  $z_{is}$ , data on cultivated land by farms  $\ell_{is}$ , and the farm information on participation in rental markets, we use our assumption on the production function to construct the marginal product of land in farms  $MPL_{is} = \gamma z_{is} \ell_{is}^{\gamma-1}$  and the participation information to construct an indicator function of non-participation for each farmer  $\mathbb{1}(\ell_{is} = \bar{\ell}_{is})$ . We use these data to construct the three moments discussed above in each state:

- $M_1^{\text{data}} \equiv \sum_{i=1}^{F_s} \mathbb{1}(\ell_{is} = \bar{\ell}_{is}) / F_s$ .
- $M_2^{\text{data}} \equiv \text{Cov}(\ln MPL_{is}, \ln z_{is})$ .
- $M_3^{\text{data}} \equiv \text{Var}(\ln MPL_{is})$ .

Note that conditional on other parameters,  $\tau_s$  influences  $M_1$ ,  $\theta_s$  influences  $M_2$ , and  $\sigma_{\epsilon s}$  influences  $M_3$ .

**Algorithm.** We follow these steps to find parameter values for distortions in each state:

1. Guess initial parameters  $(\theta_s, \sigma_{\epsilon s}, \tau_s)$ . We use  $\theta_s = 0.5$ ,  $\sigma_{\epsilon s} = 1$ , and  $\tau_s = 1$ .

2. For each  $k$  of 100 simulations, draw  $\{\epsilon_{is}^{(k)}\}_{i=1}^{F_s}$  and solve the competitive equilibrium, and compute the required moments implied by the model:

- $M_1^{(k)} \equiv \sum_{i=1}^{F_s} \mathbb{1}(\ell_{is}^{(k)} = \bar{\ell}_{is})/F_s$ .
- $M_2^{(k)} \equiv \text{Cov}(\ln MPL_{is}^{(k)}, \ln z_{is})$ .
- $M_3^{(k)} \equiv \text{Var}(\ln MPL_{is}^{(k)})$ .

3. Compute simulated moments by averaging moments from the simulations,

$$M_n^{\text{model}} = \sum_{k=1}^{100} \frac{M_n^{(k)}}{100} \quad \text{for each } n = \{1, 2, 3\}.$$

4. Compute distance  $D_n$  between data and average simulated moments,

$$D_n = M_n^{\text{data}} - M_n^{\text{model}} \quad \text{for each } n = \{1, 2, 3\}.$$

5. If  $\max\{\text{abs}(D_n)\} > \text{tol}$ , adjust parameter guesses and iterate on steps 2 - 5 until convergence.

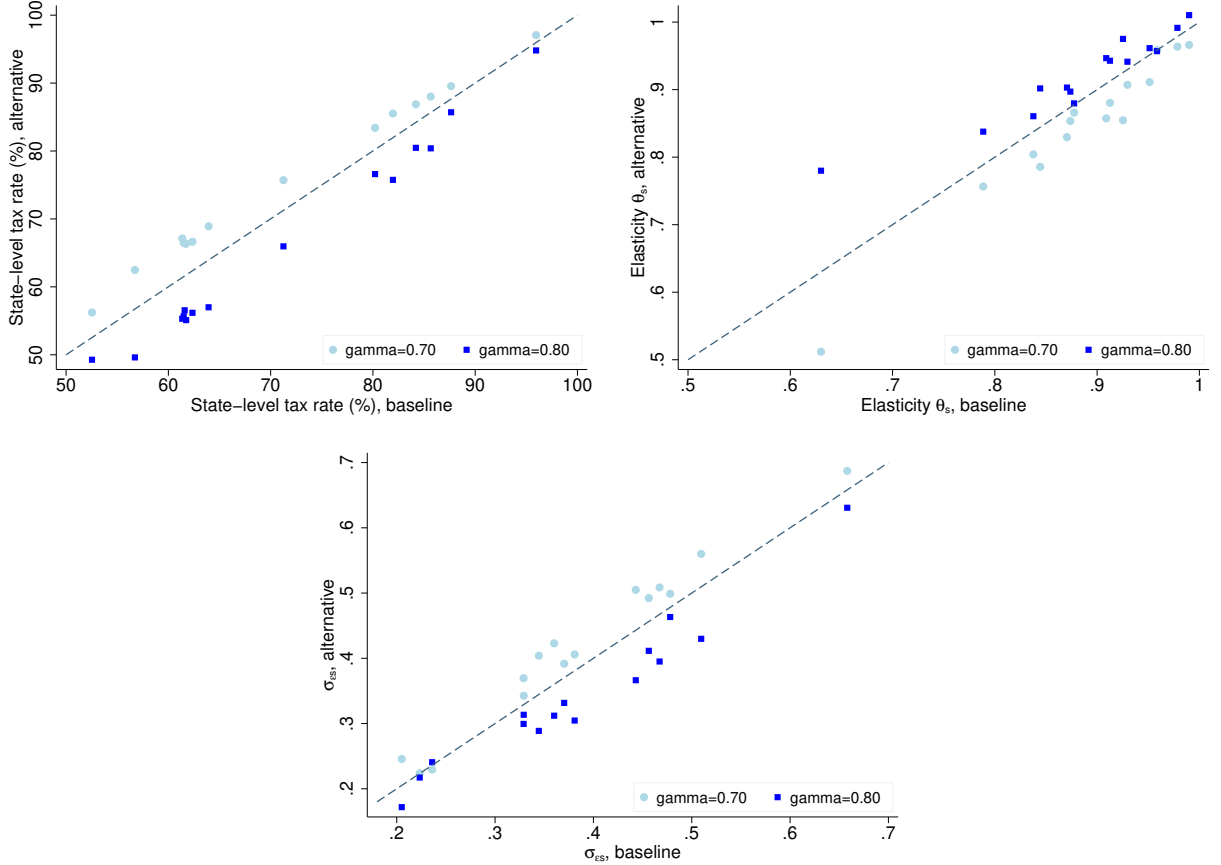
### D.3 Model Robustness

We evaluate the robustness of our model results to reasonable variations in the estimated value of the decreasing returns to scale parameter  $\gamma$ . As in the empirical section, we vary the value of  $\gamma$  from 0.75 in the baseline calibration to 0.70 and 0.80, a range of values considered in the misallocation literature.

For each value of  $\gamma$ , we re-estimate farm-level TFP in each state and re-calibrate the parameters of distortions. Figure D.6 reports the differences in estimated parameter values for each state with respect to the baseline values. As a summary, the average estimated value of  $\theta_s$  changes from 0.89 in the baseline  $\gamma = 0.75$  to 0.85 with  $\gamma = 0.70$  and 0.91 with  $\gamma = 0.80$ .

Similarly, the state-level tax associated with  $\tau_s$  changes from 71% to 75% and 66%, and  $\sigma_s$  from 0.39 to 0.42 and 0.35.

Figure D.6: Land Rental-Market Distortions for Different Values of  $\gamma$



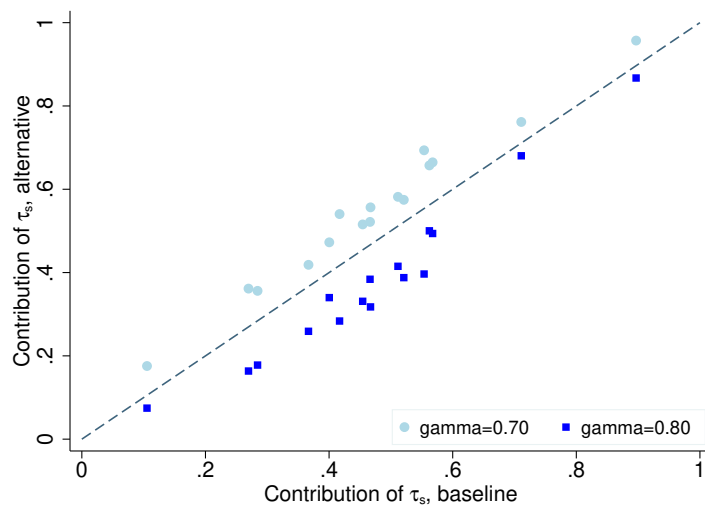
**Notes:** Panel A reports the estimated state-level rental barrier  $\tau_s$  as a tax rate on the rent-in rate, i.e.,  $\text{tax} = (1 - 1/\tau_s)$ . Panel B reports the estimated idiosyncratic distortions elasticity  $\theta_s$ . Panel C reports the estimated distortions dispersion parameter  $\sigma_{\epsilon s}$ . In all panels, the x-axis represents the value in the baseline  $\gamma = 0.75$  case, whereas the y-axis represents the alternative values ( $\gamma = 0.70$  in circles and  $\gamma = 0.80$  in squares).

For each value of  $\gamma$  we also perform the counterfactual experiments and summarize the contribution of land-market rental barriers  $\tau_s$  to the overall reallocation gains in Figure D.7. Whereas in the baseline  $\tau_s$  contributes 51 percent of the efficiency gains for India (land-weighted average across states), the contribution changes to 58 percent with  $\gamma = 0.70$  and 42 percent with  $\gamma = 0.80$ . In a highly distorted state such as Tamil Nadu, the contribution ranges from 87 to 96 percent. As emphasized earlier for other measures of misallocation,



ranking differences across states are preserved with alternative values of  $\gamma$  as documented in Figure D.7.

Figure D.7: The Contribution of Land Rental-Market Barriers for Different  $\gamma$ 's



**Notes:** Contribution to reallocation gains in fraction of state-level rental barriers  $\tau_s$  to reallocation gains. The x-axis represents the value in the baseline  $\gamma = 0.75$  case, whereas the y-axis represents the alternative values ( $\gamma = 0.70$  in circles and  $\gamma = 0.80$  in squares).