

Land Market Frictions in Developing Countries: Evidence from Manufacturing Firms in India

Aradhya Sood*

August 10, 2020

Abstract

This paper examines how land market frictions can hinder the growth of manufacturing firms in developing economies. Land market frictions are the result of increased land fragmentation, poor land records, and restrictive land use policies. Using manufacturing census from India with unique land data, I document that in regions with smaller land parcel size, firms acquire many small parcels slowly over time, expand building with 4% lower probability, and are 22% smaller in size. I build a dynamic structural model that flexibly captures firm land adjustment costs which vary with the size of adjustment and region. I find that land frictions reduce lifetime producer profits by 6.5%. In some regions, firms pay 119% in additional land aggregation costs over and above the dollar value of land. My results are also consistent with the hypothesis that government-affiliated firms face lower land frictions. I find that private firms pay *three* times more for land aggregation than government-affiliated firms. I use the model to analyze the effects of a proposed government land-pooling policy on producer profits, firm growth, and land misallocation; and to quantify the expected losses to firms from the 2015 eminent domain restrictions.

JEL Codes: D25, R52, O14

Keywords: Land Misallocation, Fragmentation, Land Frictions, Adjustment Costs, Manufacturing, India

*Federal Reserve Bank of Boston and University of Toronto. Email: aradhya.sood@utoronto.ca. This paper is a chapter of my dissertation. I thank my advisors Thomas J. Holmes, Amil Petrin, and Joel Waldfogel for their guidance and support. This paper has also benefited from discussions with Jonathan Borowsky, Sergiy Golovin, John E. Kumcu, Joseph Mullins, James Schmitz, Matt Shapiro, Dominic Smith, Kevin Williams and seminar participants at University of Minnesota, University of Toronto, University of Wisconsin (Madison), University of Utah (Business), Ohio State University, Urban Economics Association, Online Spatial and Urban Seminar, and Southern Methodist University. The remaining errors are my own.

1 Introduction

Manufacturing firms are small in many developing countries.¹ Modern manufacturing requires large amounts of land, but acquiring adequate land for industrial purposes is difficult in developing countries, which may inhibit industrial development and growth. India provides a stark example of land frictions ([Economist, 2013](#)).² Although large-scale manufacturing requires a large plot of contiguous land, Indian land is fragmented into many small parcels with an average size of only 2.9 acres—almost 100 times smaller than the average U.S. parcel size (234 acres).³ Thus, the establishment of modern manufacturing facility requires negotiation with hundreds of owners, increasing the cost of bargaining and the risk of holdouts. For instance, to assemble 997 acres of land for their Nano car plant in 2005, Tata had to deal with 12,000 different owners. In contrast, General Motors’ 1984 Fort Wayne plant acquired 937 acres of land from only 29 owners.⁴ Not only is Indian land fragmented, but land aggregation is further hampered by poor land records and restrictive land use policies.⁵

In this paper, I explore the role of land frictions in inhibiting the development of manufacturing firms in India. To do so, I proceed in three steps. First, I use novel data from the Indian Manufacturing Census to document that firms acquire many small parcels of land and slowly over time. The Census covers organized manufacturing firms and is unique in separating land inputs from other capital inputs. I also show that in regions with higher land fragmentation, firms are smaller and grow at lower rates. Second, I build a dynamic structural model that flexibly captures firm land adjustment costs which vary with the size of adjustment and according to firm ownership and location. I find that land aggregation costs are large and vary substantially across ownerships and states. Third, I run counterfactual experiments to analyze the effects of a proposed government land-pooling policy—where government acts as intermediary to aggregate land—on producer profits, firm growth, and land misallocation. Land pooling policies are currently being debated across several states in India. I find that a land-pooling policy increases the profit and growth of firms signifi-

¹See ([Hsieh and Olken, 2014](#)).

²See [Govindarajan and Bagla \(2015\)](#), [Ghatak and Mookherjee \(2014\)](#) on land reforms for industrialization.

³[MacDonald et al. \(2013\)](#)

⁴[Ghatak, Mitra, Mookherjee, and Nath \(2013\)](#), [Butters \(2015\)](#)

⁵See Appendix A for further details on land frictions in India.

cantly and lowers land misallocation. I also quantify the expected losses to firms from the 2015 law restricting the use of eminent domain for manufacturing purposes.

I build on recent literature studying the role of poor management, capital misallocation, and size-dependent policies in explaining the size of Indian manufacturing firms (Besley and Burgess, 2004; Bloom, Eifert, Mahajan, McKenzie, and Roberts, 2013; Hsieh and Klenow, 2009). While the qualitative nature of India’s land problem is well known, the lack of computerized data on land holdings and land transactions makes quantitative research difficult. Like Duranton, Ghani, Goswami, and Kerr (2015), I explore the effect of land misallocation on Indian manufacturing.⁶ I am able to complement their analysis by exploiting a previously unused section of the Indian Manufacturing Census data because I observe land currently owned by firms, as well as land acquired each year over a 17-year period.

The data allows me to document the effects of land market frictions. I show that Indian firms acquire land gradually over time, buying small parcels, rather than making rare lumpy investments, which I term the *small land bite strategy*. Moreover, the use of this strategy varies across region. In regions with smaller than average parcel size, firms adjust their land more often, but with smaller size. In regions with larger than average parcel size, adjustments are larger and more lumpy. Land fragmentation is also correlated with employment growth, revenue, and construction of new buildings. A one-acre decrease in average parcel size in a region results in 4% lower building expansions by firms and a 22% reduction in firm size.

I also find that private firms do small but frequent land adjustments, whereas firms affiliated with the government have large and lumpy adjustments. It is inherently difficult to know how firm development would unfold in the absence of land frictions. However, I make use of the insight that government-affiliated firms face smaller frictions due to easier access to eminent domain and land title clearing. So a comparison between private and government-affiliated firms in India can show the effects of land market frictions. In particular, I find that private firms add land which is *half* the size of land adjustment by government-affiliated firms, following the *small land bite strategy*.

I use the data to estimate a dynamic structural model of firm land adjustment using the variation in land bite strategies. I estimate the land adjustment costs separately across

⁶See literature review on how the current paper differs from Duranton et al. (2015).

regions and ownerships. India does not have an industrial land policy index for every region over time; and land aggregation costs from negotiation efforts and lawyer fees are not directly measured in the data. Thus, I instead use a *revealed preference* approach to indirectly measure land friction costs. I build a single agent dynamic discrete choice model (Rust, 1987) where firms produce, choose inputs, and decide the land adjustment in each period. I estimate industry-specific production function input elasticities to account for different land input requirements across industries (Levinsohn and Petrin, 2003).

In the model, firms choose whether and how much land to buy each period. The model expands on the current capital adjustment costs literature (see Caballero, 1999; Ryan, 2012) by incorporating both sunk and convex costs of investment. This accounts for not only infrequent land bites through sunk costs but also negotiation costs that increase exponentially in the size of adjustment, an important feature in countries with severe land fragmentation.

I find that land aggregation costs are large; and vary substantially across ownerships and states. Private establishments, which account for 86% of manufacturing firms, face land aggregation costs that are *three* times higher than those for government-affiliated firms. Furthermore, I find that land input is misallocated across firms based on ownership, with less productive government-affiliated firms owning more land than more productive private firms.

Land aggregation costs vary sharply across regions, and in some regions the estimated land aggregation costs add additional 119% to the direct monetary price of land. Heterogeneity in estimated land costs across regions emerges as additional source for regional inequality in new manufacturing business within India. In addition, this is the first paper that estimates land elasticity associated with manufacturing production. Through production function estimation, I find that land input elasticity in the Indian manufacturing sector is significant and is between 0.056 - 0.080.

Finally, using estimated parameters from the model, I run three counterfactual experiments. I start by studying the effect of the 2015 eminent domain restrictions on Indian manufacturing firms. Unlike China, which has fueled manufacturing using eminent domain (Ding, 2007), India's democratic setup results in lower use of eminent domain, although it is used occasionally as a de facto policy to circumvent land fictions. The 2015 law brought the

eminent domain use for manufacturing to a virtual halt and has been criticized for slowing industrialization (Ghatak and Ghosh, 2011). For this counterfactual, I compare government-affiliated firms that until 2015 had faced lower land aggregation costs but now face high private cost structure. I find that eminent domain restrictions lower lifetime producer profits of firms by up to 4.8%, and hence, could have played a role in slowing industrialization.

Next, I examine the growth of firms in the absence of land aggregation costs, which provides a bound to the effect of land frictions on manufacturing firms. I find that in the absence of land frictions, lifetime producer profits increase by up to 6.5% for the most productive firms, while firm growth rate increases by up to 11%.

Lastly, I study the effectiveness of the proposed land-pooling policy. To do so, I consider an experiment where I take a particular firm from a state with high land cost and move it to the state that follows the “best land practices” and has the lowest estimated land costs. I find that such a policy increases lifetime producer profits by up to 3.8% for the most productive firms. Additionally, land-pooling policy reduces land misallocation significantly by providing land to the most productive firms regardless of their ownership.

Although, this paper focuses on India due to data availability and the extensive land friction environment of the country, quantifying the effect on production from land frictions—restrictive land use policies and zoning—is important everywhere. This paper provides a framework to study the effects of land frictions in any country with adequate data availability. Additionally, while this paper focuses on incumbent firms, new manufacturing firms also enter with small initial land input and will have to face similar land aggregation costs as they grow. The rest of the paper is structured as follows. Section 2 provides the literature review while section 3 discusses the data and descriptive evidence. Section 4 and 5 lay out the structural model and empirical strategy, respectively. Results are displayed in section 6. Section 7 provides policy experiments.

2 Related Literature

This paper is related to a number of papers that have studied the issues of manufacturing in India, land market issues in India, and land friction issues around the world. The relatively

small Indian manufacturing sector has been documented and studied before. [Hsieh and Olken \(2014\)](#) suggest that large and capital intensive firms in India are highly constrained. Land is a major input for both large and capital intensive firms. [Banerjee and Duflo \(2005\)](#) and [Hsieh and Klenow \(2009\)](#) study misallocation in capital and output in Indian manufacturing sector indicating that less productive firms have higher inputs than what is optimal due to frictions.⁷ These papers do not focus specifically on land market frictions.⁸ [Duranton et al. \(2015\)](#) are first to highlight the effect of [Olley and Pakes \(1996\)](#) measure of land input misallocation on output misallocation in the manufacturing sector in India.

The present paper is different from [Duranton et al. \(2015\)](#) in four major ways. First, this paper builds a dynamic structural model to estimate land aggregation costs using revealed choices of firms. This approach allows the paper to study the effects of not only fragmentation but also a myriad of land related policies on the land aggregation cost structure. The structural estimation of this paper also allows for policy analysis. Second, this paper is the first to document the role of fragmentation in land market frictions and shows a link between fragmentation and firm *land bite* behavior. Third, this paper uses previously unused panel data with detailed land investment information to study effects on size manufacturing firms. Fourth, this paper consistently estimates the elasticity of land input into the manufacturing production function by following the control function approach methodology of [Levinsohn and Petrin \(2003\)](#).

While this paper focuses on the effect of land frictions on manufacturing sector in India, [Glaeser \(2014\)](#), [Glaeser and Ward \(2009\)](#), and [Herkenhoff et al. \(2018\)](#) study the effect of restrictive land policies on urban development and the recent slowdown in the U.S. economy. This paper also relates to studies on the role of clear property rights in development (see [Deininger and Feder, 2001](#); [Feder and Feeny, 1991](#)). Other papers have studied land fragmentation in India but only in the context of agriculture (see [Chand et al., 2011](#); [Manjunatha et al., 2013](#); [Parikh and Nagarajan, 2004](#)).⁹ [Heller \(1998\)](#) proposes the *theory of anti-commons* where many owners with the right to exclude others from a scarce resource

⁷Also see [Bau and Matray \(2019\)](#) on misallocation and FDI and [Boehm and Oberfield \(2018\)](#) who study the effect of court congestion on aggregate productivity in Indian manufacturing sector.

⁸Misallocation in the land input has been studied but mostly in the context of agriculture and outside India. See [Chen et al. \(2017\)](#), [Adamopoulos and Restuccia \(2014\)](#) and [Restuccia and Santaaulalia-Llopis \(2017\)](#).

⁹[Oldenburg \(1990\)](#) suggest land consolidation as land reform for agriculturists.

like land in India can result in underuse.

A few papers have looked at the connection between land market issues and manufacturing in India, albeit from a different point of view. Two case studies on the use of eminent domain for manufacturing purpose, [Ghatak et al. \(2013\)](#) on Tata Nano car plant (Singur) and [Dutta \(2009\)](#) on Nokia SEZ¹⁰, highlight the fraught nature of land acquisition for industry in India, even when an intermediary like government is involved.¹¹ My paper complements their analysis by quantifying the effects of eminent domain. [Ghatak and Mookherjee \(2014\)](#) develop a new method for land acquisition for industrialization and farmer compensation and [Mamidi \(2012\)](#) documents the role of small-town lawyers who act as middle-men to aggregate land in India. While these papers study different aspects of land market issues on industrialization, the current paper builds a structural model to estimate the costs of land frictions on manufacturing in India.

3 Data and Descriptive Evidence

3.1 Data

The main data source for this paper is the Annual Survey of Industries (ASI) manufacturing dataset. It has establishment level balance sheet data for manufacturers in India. It is a census of establishments with employment greater than 100 and a 1/3 to 1/2 sample of establishments with employment greater than 10. I have a panel of 28,584 establishments between 1999 and 2015. The establishments are anonymized at state level. The data provides information on an establishment's age, whether it is publicly or privately held, whether it is in urban or rural setting, and other input and output data that is commonly available in other manufacturing census datasets. However, unlike manufacturing datasets from other countries, the unique aspect of this data is that the book value of capital stock of an establishment is disaggregated into land, buildings, plants and machinery, and other fixed assets separately. Thus, I have a measure of land for each establishment separate from building.

¹⁰Special Economic Zone

¹¹Also see the theoretical research on eminent domain and the negotiation and bargaining that occurs under the threat of eminent domain [Miceli and Segerson \(2007\)](#).

Table 1: Summary Statistics for Manufacturing Establishments

Variable	Observations	Mean	Std. Dev.
Land Adds	21,882	0.44	6.54
Land Sales	6,517	0.19	1.17
Land	103,212	1.40	4.40
Buildings	101,869	2.61	14.22
Other Capital	103,937	12.99	98.55
Revenue	98,317	41.25	237.78
Labor	103,909	509.04	1104.14

Note: This tables presents summary statistics for the manufacturing establishment data available from ASI [1999-2015]. Values are in 2005 constant million U.S. Dollars.

Table 2: Illustrative Example of Land Data

	Opening Value	Addition	Revaluation	Closing Value
Firm A	100	50	0	150
Firm B	100	0	50	150

I also have opening and closing value of land and all other capital stocks. Furthermore, the data provides actual additions and deductions in capital stocks reported separately from revaluations and depreciation.¹² To see why data on actual additions and deductions is crucial, see Table 2 (also see Figure A2 in Appendix A for an example ASI data-form for land and other capital). Since addition is reported separately from revaluation, I can observe if Firm A’s increasing land value is due to actual purchase of new land rather than revaluation, which is the case for Firm B. The panel nature of the data allows this paper to construct land investment and divestment for establishments over 17-year period.

The census dataset provides data on value of land, but not prices separate from acreage. Although it would be ideal to have acreage data separate from value of land, this data limitation does not hinder my ability to estimate the negotiation and effort costs of land frictions. Even though I cannot estimate the effect of land frictions on land prices, I can

¹²I observe depreciation of land value in less then 1% of all land data.

capture these effects in my estimation. See Section 4.3 for detailed discussion on this. Table 1 give summary statistics for key data variables. On an average, land makes up about 8 % of total capital input and land purchase value is 2.3 times higher than land sale value. Figure A3 in Appendix provides the rate of establishment land investment and divestment in a cross section over time. There is significant amount of land adjustment by incumbent firms and establishments are three times more likely to adjust their land upwards than downwards.

This paper supplements the census manufacturing data with data on land fragmentation from the Agricultural Census of India (1995, 2000, 2005, and 2010) and Census of India 2001 and 2011. The Agricultural Census provides state level parcel size distribution for historically deemed “agricultural” land. This is an ideal dataset to study land parcel fragmentation in India. Land use statistics suggest that 8.7% of land is occupied in either urban, rural or industrial use, 54% is historically classified as agricultural (including fallow land), and remaining 37% of land is forests, un-culturable land and permanent pastures. No development can occur in this 37% of land due to laws or physical barriers. Assuming that the developed land of 8.7% is saturated, the only source of land for new and expanding manufacturing establishments comes from land historically used for agriculture. Thus, the agricultural census provides a good measure for fragmentation of land that is available for new development.¹³ See Appendix B for further details on Agricultural Census data.

¹³Another reason why this is a good measure for land fragmentation is that it does not include parcels that were already aggregated for large scale manufacturing and would falsely show a correlation in the data by sheer accounting.

Figure 1: Land Parcel Sample Maps across India and US

(a) India

(b) U.S.



Note: This figure presents sample land parcel maps across India and U.S. The area is roughly one square mile for each figure. The Indian figure is presents map of village Mahul Mahul from Odisha state. The U.S. figure is from outside GM assembly plant of Janesville, Wisconsin.

3.2 Land Market Frictions and Firm Land Adjustment

This section presents evidence of land market frictions and their effects on land investment behavior by firms. Figure 1 shows the extent of land fragmentation from a sample village in India and compares it to a similar area in the U.S. As can be seen from the figure, with roughly one square mile shown in each figure, Indian land is sub-divided into many small parcels often not in regular shapes. Fragmentation not only results in small land parcel size but also in many boundary lines—resulting in land wastage, irregular shape of parcels, and lack of access. This figure shows the extent of land fragmentation in India. In fact, land fragmentation in India has gotten worse over time as Indian population has grown. Figure 2 shows the average land parcel size in India over time 1970-2010 where average parcel size has dropped by half in the last 40 years.

The land market frictions have an effect on how firms adjust land and expand their establishments. I call this the *land bite strategy* of firms. This is defined as how often (*frequency of bites*) and how much land (*size of bites*) a firm invests for total land expansion. Figure 3 presents the share of firms who purchase land, but do not build on it after land expansion, indicating gradual process of land aggregation. As can be seen from the figure, about 26% of firms who buy land do not build on it for at least 3 years and 25% do not build on land for at least 5 years. Thus firms are aggregating land gradually bite by bite.

Additionally, firms aggregate land *bite by bite* before building on it—*land bites to meal*.¹⁴ Figure 4 plots the cumulative density function of build events preceded by land aggregation against the total number of land transactions needed before building.¹⁵ As can be seen from the figure, over 20% of building events require land aggregation of 3 or more land bites which can take years to aggregate.

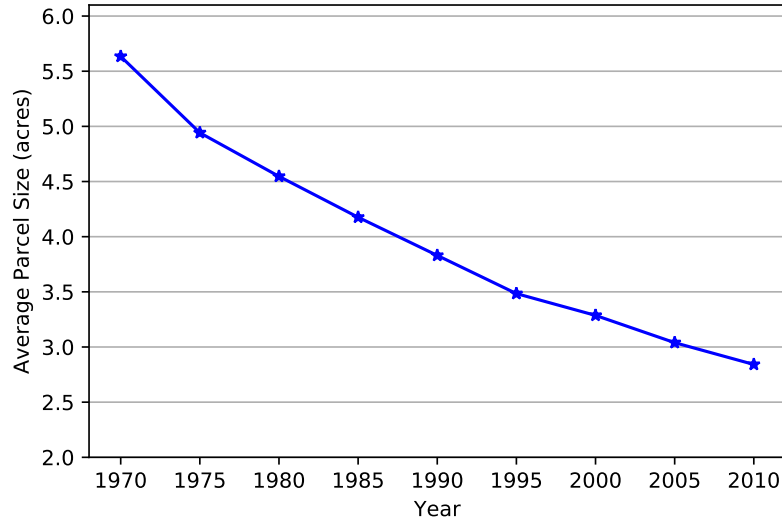
3.3 Ownership and Regional Variation in Land Bite Strategy

This section illustrates that the land bite strategy of firms varies across ownerships and regions. Below I provide three sets of evidence. First, I show that private firms compared

¹⁴Large building events are considered that would require land. These building events make up at least 20% of the mean total building value. The results are robust to different building events cut-off points.

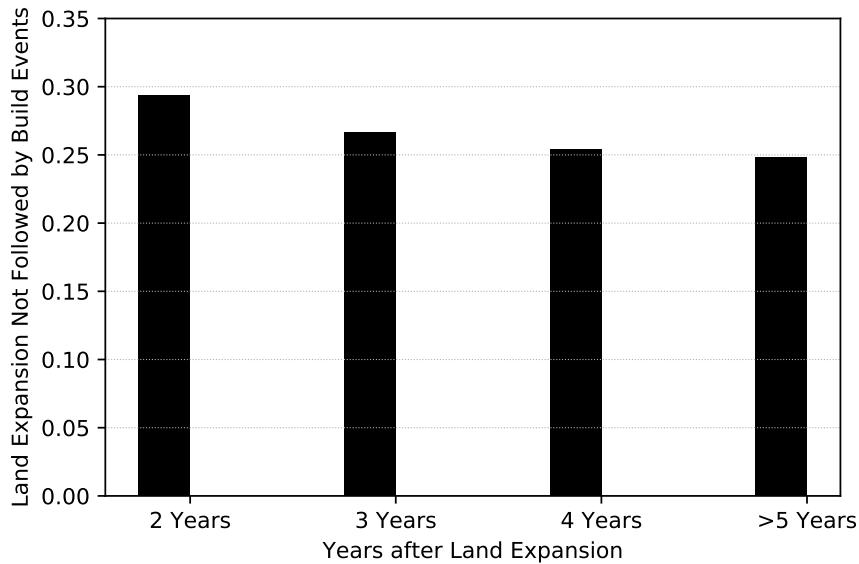
¹⁵Each of these bites may contain hundreds of actual transactions which are not observed.

Figure 2: Average Parcel Size over Time



Note: This figure presents the average land parcel size in India over time [1970-2010]. The data is from Agricultural Census of India.

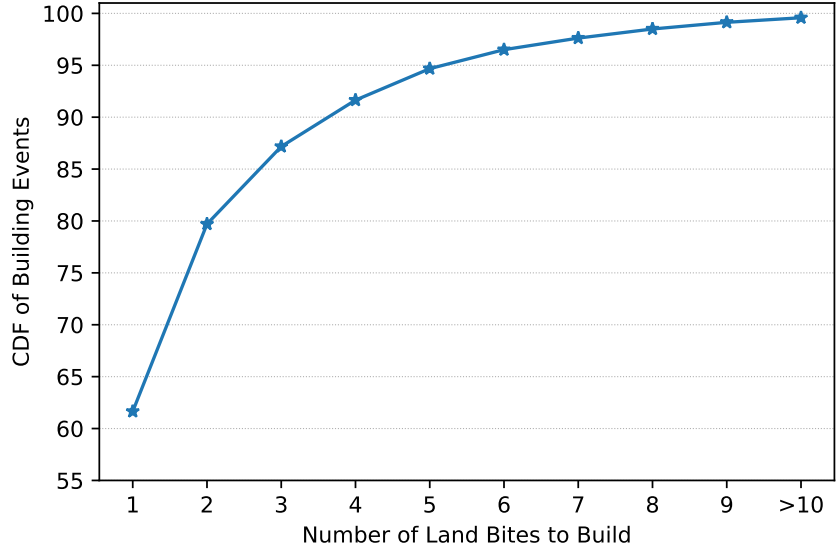
Figure 3: Time to Build—Land Expansion Not Followed by Build Events



Note: This figure presents share of firms not building after land expansion on the vertical axis and the number of years firms are holding land for on the horizontal axis [1999-2015]. The data is from ASI.

with government-affiliated firms follow the *small bite strategy* of adding land more frequently and in smaller bites. This is because government-affiliated firms have access to different land aggregation technology either through the use of eminent domain or easier re-zoning of

Figure 4: Land Bites to Meal



Note: This figure presents the percent of building events (cumulative density function) preceded by land aggregation over one land bite (or transaction) or more. Building events considered are building events are large building events requiring land. The data is from ASI [1999-2015].

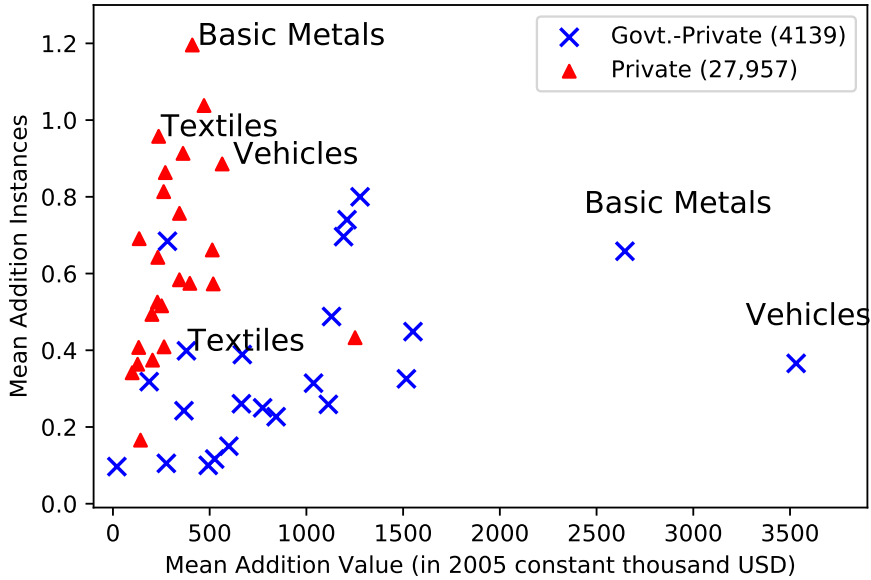
land.¹⁶ Second I show that in regions within India where land parcels are small (higher land fragmentation), firms follow the *small bite strategy*. Third, I also provide evidence that small land parcels in a region are also correlated with lower building additions and smaller firm size, as measured by labor and revenue.

3.3.1 Ownership

This section illustrates that the land bite strategy of firms varies across ownerships. I provide evidence that private firms compared with government-affiliated firms follow the *small bite strategy* of adding land more frequently and in smaller bites. Results from this section are consistent with the theory that private firms with government in India for easier land aggregation process. Figure 5 plots the mean firm land addition (mean bite size) against mean addition instances (frequency of bites) for different industries across ownership status. As it can be seen from the figure, private establishments across industries are more likely to

¹⁶Given that establishments are anonymized, I cannot determine whether a particular establishment was setup on land aggregated using eminent domain.

Figure 5: Land Bite Strategy across Ownership



Note: This figure presents the land investment behavior (or land bite strategy) of firms varied across ownership status and 2 digit industry codes [1999-2015]. The horizontal axis is mean land addition value in 1000 USD 2005 constant prices. The vertical axis is mean land addition instances. Establishments are either fully private owned or jointly owned by government and private parties. The data is from ASI.

add land in smaller and frequent bites as opposed to government-affiliated establishments. This is not due to industrial compositional differences across ownerships. For instance, compare the land bite strategy across ownerships for basic metals and vehicles industries. While government affiliated firms in the basic metals and vehicles industry add less often and with a higher land value on average, private firms in the basic metals and vehicles add land more often and with a much smaller mean land value. Figure A4 in the Appendix presents the land adjustment density of firms varied across ownership status.

The empirical approach for examining the impact of ownership status on firm land bite strategy is as follows.

$$Y_{ijt} = \beta_0 + \beta_1 \mathbb{1}Private_{ijt} + \Gamma_1 X_{1it} + \Gamma_2 X_{2jt} + \eta_2 t + \epsilon_{ijt} \quad (1)$$

Let Y_{ijt} be (i) land investment conditional on positive land adjustment or (ii) dummy for positive land adjustment by firm i in state j at time t . Let $\mathbb{1}Private_{ijt}$ be 1 if the firm is

Table 3: Land Bite Strategy across Ownership

	Land Purchases (1)	Purchase Probability (Logit) (2)
Private	-480.69*** (172.24)	0.09*** (0.03)
N	19,964	142,543
R^2	0.014	0.047
dy/dx		0.01*** (0.00)
Firm Controls	Y	Y
State Controls	Y	Y
Time Trend	Y	N
Cluster S.E.	Y	Y

Note: This tables presents results from equations 1. Specification 1 studies correlation between firm land investment and firm ownership conditional on positive land adjustment. Specification 2 studies correlation between positive land adjustment and firm ownership. ***p < 0.01, **p < 0.05, *p < 0.10. dy/dx shows the marginal effect on positive land adjustment probability of change in ownership status. Standard errors are clustered at firm ownership level. Firm controls include labor, revenue, age, and dummy for industry at 2 digit level. State controls include number of active manufacturing firms in a state, dummy for urban regions, and a dummy for state. They also include share of workers, share literate population, share urban population and population density at state level from Census 2001 and 2011. The manufacturing establishment data (1999-2015) is from ASI. The land investment is in 2005 thousand USD constant value.

owned privately. Let X_{1it} denote a vector of firm controls which includes labor, revenue, age, and 2-digit industry code dummy variable. Let X_{2it} denote a vector of location controls which includes number of active manufacturing firms in a state, dummy for urban regions, a dummy for state, and share of workers, share literate population, share urban population and population density at state level. Standard errors are clustered at firm ownership level. η_2 captures time trend. Land investment is in 2005 thousand USD constant value. The results are presented in Table 3. Specifications 1 and 2 are repeated cross-sections.

Specification 1 studies the correlation between land investment, conditional on positive land adjustment, and ownership. Specifications 2 is a logit model between probability of making positive land adjustment and firm ownership. The coefficient of interest is β_1 . If

$\beta_1 < 0$ in specifications 1, then private firms adjust land with smaller value than government-affiliated firms. As can be seen from Table 3, private firms adjust land with lower \$481,000 on average than government-affiliated firms. To put this number into context, the mean land addition is \$444,000 in value. If $\beta_1 > 0$ in specification 2, then private firms adjust land with higher probability than government-affiliated firms. As can be seen from Table 3, in a given period, private firms adjust land with higher probability of 1% compared to government-affiliated firms. Thus, private firms follow the *small bite strategy* by adding land more frequently but with smaller land bites.

3.3.2 Region

This section illustrates that the land bite strategy of firms varies across regions (states) within India. It shows that in regions within India where land parcels are small—higher land fragmentation, firms follow the *small bite strategy*. Table 4 ranks states by average land parcel size (acres) in state from lowest to highest. It also shows the average firm land bite size and the percent of build events preceded by 3 or more land bites across states. As can be seen from the table, in states with smaller land parcels like Bihar and West Bengal, firms adjust land with smaller bites and do so by aggregating over many land bites over time. In Bihar 57.4% of build events require land aggregation over three or more bites. In states with larger land parcels like Punjab and Rajasthan, firms adjust land with larger bites and do so aggregating over fewer land bites.¹⁷ Thus, in regions within India where land parcels are small, firms follow the *small bite strategy*.

This is also true across industries and after controlling for various other factors. The empirical approach for examining the impact of land fragmentation on firm land bite strategy is as follows.

$$y_{ijt} = \beta_0 + \beta_1 f_{jt} + \Gamma_1 X_{1it} + \Gamma_2 X_{2jt} + \eta_2 t + \epsilon_{ijt} \quad (2)$$

Let y_{ijt} be land investment (including no land investment) by firm i in state j at time t . f_{jt} is either (i) average land parcel size, (ii) number fragmentation index or (iii) area fragmentation

¹⁷Figure A5 in the Appendix presents the land adjustment density of firms across states and shows how they differ.

Table 4: Firm’s Land Bite Strategy across States

State	Mean Parcel Size (acres)	Mean Bite Size (\$1000)	Percent of Build with 3 or more Bites
Bihar	0.43	256	57.4
West bengal	0.79	516	37.5
Uttar Pradesh	0.80	958	24.1
Tamil Nadu	0.83	757	30.8
Assam	1.11	140	66.6
Andhra Pradesh	1.20	660	27.1
Maharashtra	1.46	1722	17.1
Chhattisgarh	1.51	1538	24.7
Karnataka	1.63	1648	18.8
Madhya Pradesh	2.02	1057	23.5
Gujarat	2.20	1646	18.7
Haryana	2.24	1570	24.8
Rajasthan	3.39	1305	21.6
Punjab	3.95	1047	23.4

Note: This tables presents the average land parcel size across states along with average land bite strategy of manufacturing firms across states. The average parcel size of a state is from 2005 Agricultural Census of India and manufacturing establishment data (1999-2015) is available from ASI. The land investment is in 2005 thousand USD constant value.

index in state j at time $t = 2000, 2005, 2010$. The number and area fragmentation indices measure the share of state’s land within a parcel size bin. Higher the number in the index, the lower the fragmentation in a location. See Data Appendix B for details on the fragmentation index construction. Let X_{1it} denote a vector of firm controls which includes labor, capital, age, ownership status and 2-digit industry code dummy variable. Let X_{2it} denote a vector of location controls which includes number of active manufacturing firms in a state, dummy for urban regions, and share of workers, share literate population, share urban population and population density at state level. η_2 captures the time trend. Standard errors are clustered at state level. Land investment is in 2005 thousand USD constant value.

The results are presented in Table 5. This is a repeated cross-section model over three time years. The coefficient of interest is β_1 . If $\beta_1 > 0$, then firms aggregate land in larger bites in states with lower land fragmentation. As can be seen from Table 5, an increase in average parcel size of 1 acre, increases the value of land adjustment by \$15,130. The results

Table 5: Firm’s Land Bite Strategy and Fragmentation

	Land Purchases (1)	Land Purchases (2)	Land Purchases (3)
Fragmentation Measure	Average Parcel Size (acres)	Number Index	Area Index
Fragmentation	15.31** (7.19)	15.17* (7.68)	8.06** (3.68)
N	21,496	21,496	21,496
R ²	0.036	0.036	0.036
Firm Controls	Y	Y	Y
State Controls	Y	Y	Y
Time Trend	Y	Y	Y
Cluster S.E.	State	State	State

Note: This tables presents results from equations 2 on the correlation between firm land investment and regional land fragmentation. Specification 1 uses average land parcel size as a measure of fragmentation, specifications 2 and 3 use number and area fragmentation index, respectively. These are repeated cross-sections for years. ***p < 0.01, **p < 0.05, *p < 0.10. Standard errors are clustered at state level. Firm controls include labor, revenue, age, ownership status, and dummy for industry at 2 digit level. State controls include number of active manufacturing firms in a state, dummy for urban regions, and share of workers, share literate population, share urban population and population density at state level from Census 2001 and 2011. The fragmentation data is from years 2000, 2005, and 2010 Agricultural Census of India and manufacturing establishment data (1999-2015) is from ASI. The land investment is in 2005 thousand USD constant value.

are robust to different measures of fragmentation. The number fragmentation index measure provides similar results to the average land parcel size measure. Moving one point up in the area fragmentation index increases the value of land adjustment by \$8,060. To put these numbers in context, the mean land addition is \$444,000 in value. Thus, in regions within India where land parcels are small, firms follow the *small bite strategy* and aggregate land in smaller bites.

3.4 Fragmentation and Firm Growth

Land fragmentation not only has an effect on how and when firms aggregate land but also on firm size and whether firms expand their building infrastructure. The empirical approach for

Table 6: Firm Growth and Fragmentation

	Building Addition (1)	Log Labor (2)	Log Revenue (3)
Average Parcel Size	0.19** (0.08)	0.19*** (0.06)	0.33** (0.12)
N	19,095	21,474	19,091
R^2	0.062	0.344	0.287
dy/dx (at mean)	0.04*** (0.00)		
Firm Controls	Y	Y	Y
State Controls	Y	Y	Y
Time Trend	Y	Y	Y
Cluster S.E.	State	State	State

Note: This tables presents results from equations 3 on the correlation between regional land fragmentation and firm building expansion and size. Specification 1 is a logit model for the probability of building expansion that requires land. Specifications 2 and 3 are linear regression models. These are repeated cross-sections over years. ***p < 0.01, **p < 0.05, *p < 0.10. Standard errors are clustered at state level. dy/dx shows the marginal effect on building expansion probability at mean average parcel size. Firm controls include labor, capital, revenue, age, ownership status, and dummy for industry at 2 digit level. State controls include number of active manufacturing firms in a state, dummy for urban regions, and share of workers, share literate population, share urban population and population density at state level from Census 2001 and 2011. The fragmentation data is from years 2000, 2005, and 2010 Agricultural Census of India and manufacturing establishment data (1999-2015) is from ASI.

examining the impact of land fragmentation on various firm growth variables is as follows.

$$Y_{ijt} = \beta_0 + \beta_1 \text{avg}_{jt} + \Gamma_1 X_{1it} + \Gamma_2 X_{2jt} + \eta_2 t + \epsilon_{ijt} \quad (3)$$

Let Y_{ijt} be either (i) dummy for positive building adjustment by firm i in state j at time t , (ii) firm size as measured by log labor, and (iii) firm size as measured by log revenue. Building events considered are large building events that would require land.¹⁸ avg_{jt} is average land parcel size in a state at time $t = 2000, 2005, 2010$. Let X_{1it} denote a vector of firm controls which includes capital, age, ownership status and 2-digit industry code dummy variable. Let X_{2it} denote a vector of location controls which includes number of active manufacturing

¹⁸The results are robust to different building events cut-off points.

firms in a state, dummy for urban regions, and share of workers, share literate population, share urban population and population density at state level. η_2 captures the time trend. Standard errors are clustered at state level. This is a repeated cross-section model over three years. The results are presented in Table 6. Specification 1 is a logit model for the probability of building expansion.

The coefficient of interest is β_1 . If $\beta_1 > 0$, then lower land fragmentation is positively correlated with various measures of firm growth. As can be seen from Table 6, an increase in average parcel size of 1 acre increases the probability of building expansion by 4%. An increase in average parcel size of 1 acre increases the firm size (labor) by 22% and firm size (revenue) by 39%. These results are robust to different measures of fragmentation. Thus, land fragmentation is not only correlated with firm’s land bite strategies but also with firm size and firm building expansion probability.

3.5 Taking Stock

In the previous section, I provided descriptive evidence of land frictions and how it affects firm land expansion and growth. Land frictions are correlated with firm *land bite strategy*, probability of building expansion, and firm size. In particular, higher land fragmentation in a region is correlated with *small land bite strategy* of firm land expansion. Additionally, I provide evidence that government-affiliated firms escape some of these frictions and adjust their land with large and less frequent bites. Moving forward, I use a dynamic firm land acquisition model to quantify costs of land market frictions on manufacturing firms in India. In particular, I estimate negotiation and effort costs of land aggregation across ownerships and states. Using my estimated results, I do policy experiments.

4 Model

The dynamic discrete choice model uses panel data to recover land adjustment costs from establishment’s dynamic land purchase decisions. Incumbent establishments make land investment and disinvestment decisions every period to adjust their land input. Establishments make land adjustment decisions both on intensive and extensive margin i.e. they

decide whether to buy land and if so, by how much. Establishment decisions depend on firm productivity, industry, ownership, and regional land market friction environment they are facing. Thus, firms take their land market environment as given. The model estimates parameters associated with fixed and convex costs of land purchase decisions across locations and ownership status.

4.1 State Variables and Timing

Time is discrete and each decision period is one year. The state variables are land ℓ and establishment productivity z . The timing of the model is given as:

1. State variable land is carried over from last period and productivity is realized
2. Land purchase or sale decision shocks are realized.
3. Incumbents make land adjustment decisions.
4. State vector of land adjusts deterministically if land purchase or sale was made.
5. Per period profits are realized.

4.2 Payoff Function

The production function for an establishment i in industry s is given by the following Cobb-Douglas function:

$$f_{is}(\ell, k, n, e) = z_i p_s \ell_i^{\alpha_{1s}} n_i^{\alpha_{2s}} k_i^{\alpha_{3s}} e_{1i}^{\alpha_{4s}} e_{2i}^{\alpha_{5s}} e_{3i}^{\alpha_{6s}} \quad (4)$$

where z is productivity, ℓ is land, n is labor, k is capital, and e_1 is materials, e_2 is energy and e_3 is fuel. In a time period, the firm pays for labor wages w , capital r , materials p_{e1} , energy p_{e2} , and fuel p_{e3} . Payment for land input is done if and when land is acquired. The per period profit function of an establishment $\bar{\pi}_{is}$ is given by:

$$\bar{\pi}_{is}(\ell, z; \alpha) = z_i p_s \ell_i^{\alpha_{1s}} n_i^{\alpha_{2s}} k_i^{\alpha_{3s}} e_{1i}^{\alpha_{4s}} e_{2i}^{\alpha_{5s}} e_{3i}^{\alpha_{6s}} - w_i n_i - r k_i - p_{e1} e_{1i} - p_{e2} e_{2i} - p_{e3} e_{3i} \quad (5)$$

4.3 Land Adjustment Cost Function

The land adjustment cost function captures the effects of key land market frictions faced by manufacturing establishments depending on their location and ownership. These are costs associated with holdout, negotiation, re-zoning delays, undefined property rights, fuzzy land records, and time costs from slow moving courts that are not observed in the data. To capture the observed data feature that establishments do not adjust land every period, the model builds in sunk costs in the land adjustment process that discourage establishments from adjusting land in small bites incrementally every period. To capture the effect of land fragmentation and the consequent increase in bargaining and holdout issues, the paper adds a curvature (convex) parameter to the cost function. In addition, the costs from land friction wedges are part of the land adjustment cost function.

Let m_{it} be the land adjustment in period t by firm i . If $m_{it} > 0$, establishments invest in land. If $m_{it} < 0$, establishments divest their land input. The land adjustment cost function for plant i is given by $C(m_{it}; \gamma_j)$ where j represents either different states across India or different ownership status.

$$C(m_{it}; \gamma_j) = \mathbb{1}_{m_{it} > 0} \left(\gamma_{0j} + (1 + \gamma_{1j}) m_{it}^{1+\gamma_{2j}} \right) + \mathbb{1}_{m_{it} < 0} \left(\gamma_{3j} + (1 + \gamma_{4j}) m_{it}^{1+\gamma_{5j}} \right) + \epsilon_{im_t} \quad (6)$$

The fixed cost parameters are γ_{0j} and γ_{3j} . The land friction wedge parameters are γ_{1j} and γ_{4j} with the restriction that $\gamma_{1j}, \gamma_{4j} \geq 0$. The curvature (convex) parameters are given by γ_{2j} and γ_{5j} . There are no restrictions on the curvature parameters. $\gamma_{2sj} \geq 0$ is evidence of convex land aggregation costs.

Let $\vec{\gamma}_j$ denote the vector of land cost parameters for brevity. Given that firms are three times more likely to buy land than to sell it (see Figure A3), the land adjustment cost function also captures the feature that costs associated with investment are different from costs associated with disinvestment. The paper does not have a prior on the sign of γ_{5sj} , the parameter associated with the curvature costs from land disinvestment. It's possible that the sale gains from selling larger amounts of land is positive, where firms are reaping benefit of selling already aggregated land.

Every period, the establishment also draws an extreme value i.i.d logit draw ϵ_{imt} associated with both the intensive (how much land to buy) and extensive margin of land adjustment. Shock ϵ_{i0} is associated with no land investment $m_{it} = 0$. The logit structural error term is meant to capture scenarios such as a parcel of land is available for sale right next to a firm but this is not observed by the econometrician.

Note that m_{it} is value of land, price times acreage. As such, if there are any effects of land frictions on land prices, they are already captured in the observed m_{it} from the data. Parameters $\vec{\gamma}_j$ estimate non-price time and effort costs of land frictions. If there were no non-price costs from land market, then the land cost function would be $C(m_{ist}) = m_{ist}$ i.e. the dollar value of land purchase observed in the data is the true cost of land aggregation. This would be equivalent to setting $\vec{\gamma}_j$ to 0.

4.4 Value Function

The incumbents are deciding between no land adjustment, land purchase or land sale. The value function for the incumbent firm is given by:

$$\begin{aligned}
V_i(z, \ell) = \max \left\{ \right. & \left[\underbrace{\epsilon_{(m_i=0)} + \bar{\pi}_{ij}(\ell, z; \alpha) + \beta \mathbb{E}_{\epsilon, z} V_i(z', \ell)}_{\text{no land adjustment}} \right], \\
& \max_{m_i > 0} \left[\left(-\gamma_{0sj} - (1 + \gamma_{1sj}) m_{ist}^{1+\gamma_{2sj}} + \epsilon_{(m_i > 0)} \right) \right. \\
& \left. \underbrace{+ \bar{\pi}_{ij}(\ell + m_i, z; \alpha) + \beta \mathbb{E}_{\epsilon, z} V_i(z', \ell + m_i)}_{\text{positive land adjustment}} \right], \\
& \max_{m_i < 0} \left[\left(-\gamma_{3sj} - (1 + \gamma_{4sj}) m_{ist}^{1+\gamma_{5sj}} + \epsilon_{(m_i < 0)} \right) \right. \\
& \left. \underbrace{+ \bar{\pi}_{ij}(\ell - m_i, z; \alpha) + \beta \mathbb{E}_{\epsilon, z} V_i(z', \ell - m_i)}_{\text{negative land adjustment}} \right] \left. \right\}, \tag{7}
\end{aligned}$$

4.5 Land Adjustment at Extensive and Intensive Margin

In the model, establishments make land adjustment decisions on the intensive and extensive margins i.e. they choose whether to buy land and by how much. These decisions are

induced by the firm's productivity z , which follows a Markov process, and the i.i.d logit structural error ϵ . The curvature (convex) cost parameter affects the intensive margin of land investment. Presence of convexity ($\gamma_{2j} > 0$) reduces the optimal amount of land investment. Thus in regions or ownerships where convex costs are high, establishments will adjust less in each period—smaller bites.

While productivity and curvature convex costs determine the level of land adjustment, whether an establishment chooses to adjust depends on the fixed costs. A firm will adjust land upwards if the benefit of doing so outweighs the costs:

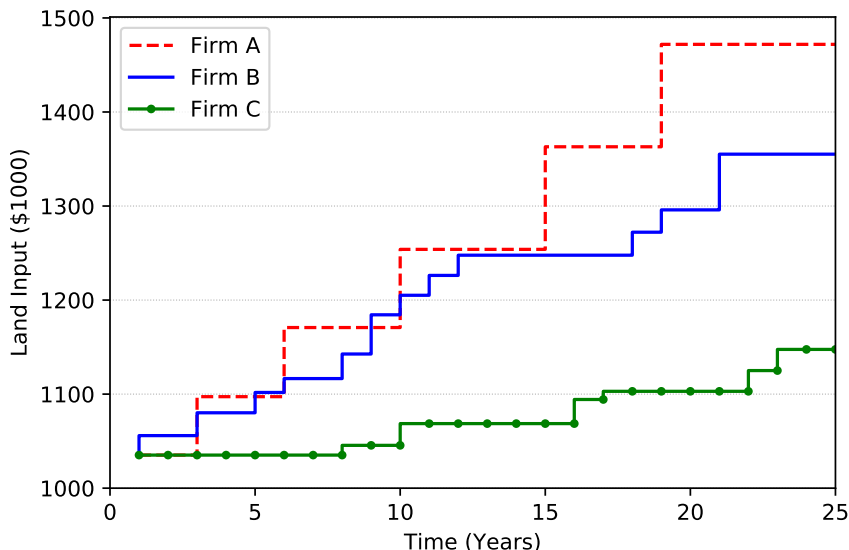
$$\max_{m_i > 0} \left[\left(-\gamma_{0j} - (1 + \gamma_{1j})m_{it}^{1+\gamma_{2j}} + \epsilon_{(m_i > 0)} \right) + \bar{\pi}_{ij}(\ell + m_i, z; \alpha) + \beta \mathbb{E}_{\epsilon, z} V_i(z', \ell + m_i) \right] \geq \left[\epsilon_{(m_i = 0)} + \bar{\pi}_{ij}(\ell, z; \alpha) + \beta \mathbb{E}_{\epsilon, z} V_i(z', \ell) \right] \quad (8)$$

Lets substitute the optimal land function for next period's land, $\ell^*(\ell)$, to get rid of the maximum in equation 8. Note that $\ell^*(\ell) = \ell + m$. The optimal land function for next period $\ell^*(\cdot)$ depends on current land level ℓ . This is an outcome of the curvature costs in the land adjustment cost function. Rearranging terms in 8, we get:

$$\beta \left(\mathbb{E}V(z', \ell^*(\ell)) - \mathbb{E}V(z', \ell) \right) + \left(\bar{\pi}_{ij}(\ell^*(\ell)) - \bar{\pi}_{ij}(\ell) \right) \geq \gamma_{0j} + (1 + \gamma_{1j}) \left(\ell^*(\ell) - \ell \right)^{1+\gamma_{2j}} + (\epsilon_{(m_i = 0)} - \epsilon_{(m_i > 0)}) \quad (9)$$

If optimal adjustment needed is small, such that $\ell^*(\ell) \approx \ell$, then L.H.S in equation 9 is close to 0 and is less than R.H.S. Presence of fixed costs (γ_{0sj}) result in inaction in certain ranges of optimal land input which is too close to current land input. This generates lumpiness and establishments do not adjust land every period (see [Caballero, 1999](#)). Note that increase in fixed costs γ_0 will increase the RHS value, thus increasing the band of inactivity resulting in lesser land expansion on the extensive margin. Increase in the logit shock associated with extensive margin of land adjustment ($\epsilon_{(m_i = 0)}$) results in fewer land expansions while increase in the intensive margin of land adjustment logit error ($\epsilon_{(m_i > 0)}$) results in more land expansion.

Figure 6: Identification of Land Aggregation Cost Parameters



Note: This figure plots the difference in land input growth across three firms that adjust land in presence of land aggregation fixed and convex costs. All three firms are privately owned, in the basic metals industry, and are located in three different states.

5 Empirical Strategy

The paper estimates the key land aggregation cost parameters in two distinct steps. First, I estimate the production function using [Levinsohn and Petrin \(2003\)](#) to get consistent production function estimates, including an estimate for land elasticity and an estimate of firm-specific residual productivity over time. Second, I estimate the land cost function parameters using the nested-fixed point algorithm following [Rust \(1987\)](#). This section lays out the identification for the model as well as the empirical strategies for these two steps.

5.1 Identification of Land Cost Parameters

The identification of the land cost parameters comes from regional and ownership variation in firm land bite strategies, as seen in Section 3. To see how the fixed and convex costs are identified, refer to Figure 6. This figure lays out the growth of land input for three firms with same initial land input and same initial productivity. However, each of these firms face different land aggregation costs. Firm A faces lower convex costs (γ_2), and hence, adjusts

it's land input with big bites. This can be seen in the height of the steps for Firm A in the figure. Firm B faces higher convex costs (γ_2) but lower fixed costs (γ_0), and hence, adjusts it's land input with small but frequent bites. This can be seen in the many small steps taken by Firm B in the figure. Firm C faces higher convex costs (γ_2) and higher fixed costs (γ_0), and hence, adjusts it's land input with small and infrequent bites. Differences in land bite strategies across regions and ownerships helps identify both sunk and convex costs of land aggregation.

5.2 Production Function Estimation

I estimate the production function parameters and productivity \hat{z}_t using the control function approach as laid out by [Levinsohn and Petrin \(2003\)](#). This method has multiple facets that allow me to consistently estimate parameters, including the land input elasticity. First, following [Olley and Pakes \(1996\)](#), this paper uses the control function approach to account for endogeneity issues arising from unobserved firm productivity. Secondly, the [Levinsohn and Petrin \(2003\)](#) approach uses input materials (materials, fuel, or energy) instead of investment in land and/or capital, for which I observe mostly non-zero values in the data. In the production function estimation, I use three state variables: land ℓ , productivity z , and capital k .¹⁹ This also allows me to account for endogeneity issues with both land and capital which are both not freely adjustable variables.²⁰ This paper uses materials, fuel, and energy as proxy variables for both land and capital.

For production function estimation, I first take the log of the production function in equation (4).

$$\begin{aligned} \log y_{it} = & \alpha_{0s} + \alpha_{1s} \log \ell_{it} + \alpha_{2s} \log n_{it} + \alpha_{3s} \log k_{it} \\ & + \alpha_{4s} \log e_{1it} + \alpha_{5s} \log e_{2it} + \alpha_{6s} \log e_{3it} + \omega_{it} + \epsilon_{it} \end{aligned} \quad (10)$$

¹⁹The model does not have capital as a state variable. To be consistent with that, I have also estimated residual productivity and production function elasticities with land and productivity as the only state variables. Results from this alternative specification do not change the land aggregation cost parameters as long as land elasticity is estimated consistently.

²⁰Decisions to adjust land and capital in this period, which determines the inputs of next period, is based this period's productivity.

where $\omega_{it} = \log z_i$. e_{1i} materials and e_{2i} energy are assumed to be variables and non-dynamic inputs like labor. Assume that the establishment does not observe ω_{it} when the materials, fuel, and energy decisions are made. Then firm's optimal choice of materials e_{1i} is $\log e_{1i} = g_t(\log \ell_{it}, \log b_{it}, \omega_{it})$. Assuming strict monotonicity, this equation can be inverted and substituted into the production function:

$$\log y_{it} = \alpha_{2s} \log n_{it} + g_t(\log \ell_{it}, \log b_{it}, \omega_{it}) + \alpha_{5s} \log e_{2it} + \alpha_{6s} \log e_{3it} + \epsilon_{it} \quad (11)$$

where

$$g_t(\log \ell_{it}, \log b_{it}, \omega_{it}) = \alpha_{0s} + \alpha_{1s} \log \ell_{it} + \alpha_{3s} \log b_{it} + \alpha_{4s} \log e_{1it} + \omega_{it}(\log \ell_{it}, \log b_{it}, e_{1it}) + \epsilon_{it} \quad (12)$$

I estimate consistent estimates of α_{2s} , α_{5s} and α_{6s} in the first stage. I estimate α_{1s} , α_{3s} and α_{4s} in second stage using GMM. The standard errors are estimated using the bootstrap method. Once, the production function elasticity estimates are calculated, I also estimate the firm-specific productivity as a residual from the production function. This provides an estimate of firm productivity for each establishment over time. This paper uses the estimated productivity residuals to estimate a data-driven Markov transition probability matrix for the region and ownership specific productivity processes.

Separately identifying the input elasticities of land and capital allows for a well defined elasticity of substitution between land and capital. It is also crucial to estimate in a study of firm land adjustment costs.

Additionally, as mentioned above, the production function elasticities are measured separately for each industry s . This accounts for the fact that a car plant might have a higher land input elasticity than a textile plant. In this paper, I estimate the production function separately for the 10 largest industries where industries are defined at the 2-digit codes level (see Table [A2](#) for the list of industries studied).

5.3 Estimation of Land Cost Parameters

The empirical specification of the model is described in this section. Firms discount the future at rate $\beta = 0.95$ and each decision period is one year. The continuous decision of how much land to buy is discretized. Each establishment draws an extreme value logit i.i.d land adjustment draw ϵ_{ib} . Index b ($b = 0, \dots, B$) corresponds to discrete adjustment levels of land where $b > 0$ if firm buys land. ϵ_{i0} is the shock associated with no land investment $m_{ib} = 0$. Thus, the logit error term is associated with both the intensive and extensive margin of land adjustment. The empirical specification is given by:

$$V(z, \ell) = \max_b \{u(z, \ell, b) + \beta \mathbb{E}_{\epsilon_{b,z}} V_i(z', \ell', \epsilon')\} \quad (13)$$

where $u(z, \ell, b)$ is given below and D is non-land inputs into production function.

$$u(z, \ell, b) = \left\{ \begin{array}{ll} \hat{z}D(\ell + m_b)^{\hat{\alpha}_1} - \gamma_{0sj} - m_b^{1+\gamma_{2sj}} + \epsilon_{(m_{ib}>0)} & \text{if } b > 0 \\ \hat{z}D(\ell)^{\hat{\alpha}_1} + \epsilon_{(m_{ib}=0)} & \text{if } b = 0 \end{array} \right\} \quad (14)$$

I estimate the land cost parameters using the nested fixed point approach and maximum likelihood estimation. I discretize the state space of state variables ℓ, z for this process.

Baseline Specification:

In the baseline estimation, I assume that sales are a random shock to land input and do not estimate the land adjustment cost parameters associated with land sale. I also set the land friction wedge parameter $\gamma_{1j} = 0$. The land cost parameters I estimate in the baseline specification are γ_{0sj} and γ_{2sj} for j different states and 2 different ownerships.²¹ In an alternative specification, I set $\gamma_{2j} = 0.01, 0.02, 0.03$ instead and estimate γ_{0sj} and γ_{1sj} . This alternative specification gives similar results in fitted dollar values (see Appendix).

In the baseline specification, adjustment levels are discretized to 5 levels for investment, giving firms 6 total choices. In the alternative specifications, adjustment levels are discretized

²¹Both γ_{1j} and γ_{2j} cannot be identified simultaneously.

to 7 and 9 levels for investment. The results presented below are robust to different levels for investment. I estimate the land aggregation parameters for 10 largest manufacturing industries in 10 largest manufacturing states and across 2 ownership codes.

6 Results

Results from production function estimation and firm dynamic model estimation are presented in this section.

6.1 Production Function Results

The results from the first-stage estimation of production function using [Levinsohn and Petrin \(2003\)](#) are given in Table 7. As can be seen from the table, the land input coefficient ranges from 0.056 for textiles to 0.082 for vehicles, indicating that land is significant input into a manufacturing firm’s production. To the best of my knowledge, these are first land elasticity estimates for manufacturing production for any country. Land elasticity coefficient has not been measured separately from non-land capital elasticity coefficient before due to data constraints. In the literature, land elasticity is estimated at sectoral level. The estimates from this paper are consistent with such estimates on the U.S. economy (see [Nordhaus et al., 1992](#); [Valentinyi and Herrendorf, 2008](#)).²²

The OLS land elasticity estimate is about 0.04, similar to the OLS estimate of [Duranton et al. \(2015\)](#). The capital coefficient estimate, including the land input, is similar to the 0.23 elasticity estimate by [Collard-Wexler and De Loecker \(2016\)](#) who use Indian manufacturing establishment data, albeit for a different time period.²³

I also use this methodology to estimate the residual firm specific productivity over time. Productivity estimates are displayed in Table A2. These results are for the 10 largest manufacturing industries in India. The residual productivity estimates are used to estimate

²²Using aggregated sectoral data, ([Valentinyi and Herrendorf, 2008](#)) find that the manufacturing sectoral level of land share is 0.04 in the U.S. economy. ([Nordhaus et al., 1992](#)) estimated the land input share to be about 0.1 of GDP.

²³This estimate is [Collard-Wexler and De Loecker \(2016\)](#) estimate using the [Levinsohn and Petrin \(2003\)](#) methodology.

Table 7: Production Function Estimates

Industry (NIC Codes)	Labor	Land	Capital	Materials	Energy	Fuels	No. of Plants	Obs.
Chemical Products (20)	0.312 (0.017)	0.065 (0.008)	0.169 (0.051)	0.552 (0.017)	0.138 (0.052)	0.045 (0.021)	1825	7346
Textiles (13)	0.272 (0.011)	0.056 (0.012)	0.179 (0.032)	0.410 (0.181)	0.025 (0.007)	0.035 (0.012)	2738	12540
Non-Metallic Mineral (23)	0.374 (0.014)	0.071 (0.025)	0.159 (0.012)	0.534 (0.009)	0.085 (0.047)	0.028 (0.012)	2943	7270
Vehicles (29)	0.193 (0.025)	0.082 (0.019)	0.236 (0.047)	0.515 (0.079)	0.101 (0.009)	0.020 (0.005)	1140	5892

Note: This tables presents the production function estimates from Levinsohn and Petrin (2003) estimation on Indian manufacturing establishment data (1999-2015) using both land and capital as state variables. Standard errors are in parenthesis.

the productivity Markov transition matrix in the second stage estimation. The production function coefficient estimates are also used in the second stage dynamic parameter estimation.

6.2 Land Aggregation Cost Parameter Results

This section presents results on land aggregation cost parameters. Since there is enough data to estimate dynamic parameters across regions and ownerships, I estimate parameters for ten largest manufacturing states and across two ownership codes (private and government-affiliated). Table 8 presents the land aggregation cost parameter estimates across different states (Panel A) and ownership codes (Panel B). The land aggregation cost parameters are estimated for pooled 10 largest manufacturing industries in India.²⁴

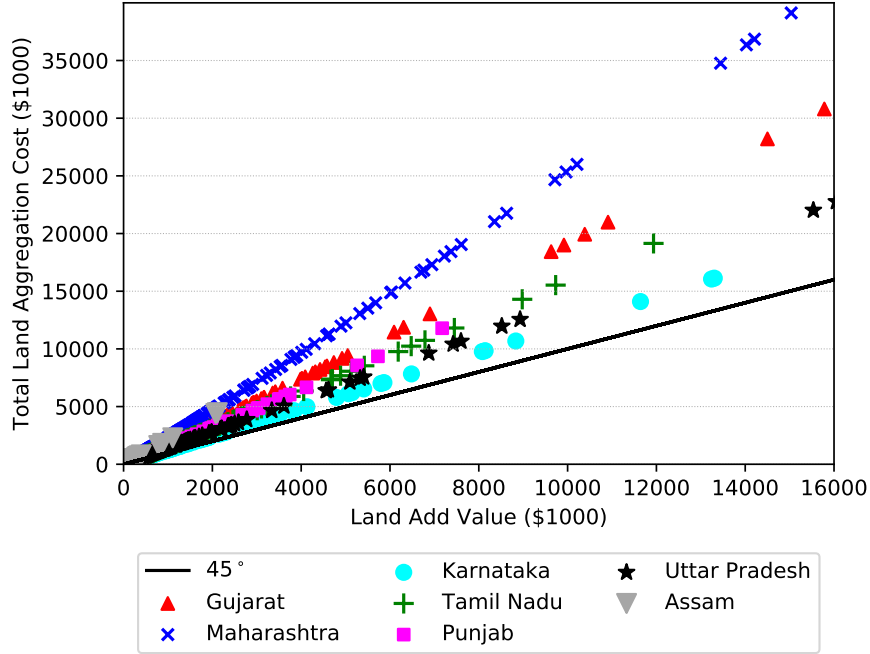
²⁴Industries are: Food Products, Textiles, Non-Metallic Minerals, Chemical Products, Basic Metals, Machinery and Equipment, Wearing Apparel, Fabricated Metals, Vehicles, and Electrical Equipment. Industry codes are listed in Table A2.

Table 8: Dynamic Parameter Estimates Across States and Ownership Codes

Panel A–States	Fixed Costs (γ_0)	Curvature Costs (γ_2)	Llk	# Obs.
Gujarat (GJ)	21.934 (1.964)	0.0403 (0.0007)	-12812	6274
Maharashtra (MH)	43.602 (0.935)	0.0578 (0.0008)	-13899	9625
Karnataka (KA)	66.408 (1.497)	0.0115 (0.0044)	-3523	2879
Tamil Nadu (TN)	61.453 (0.756)	0.0288 (0.0007)	-11034	8566
Punjab (PN)	31.781 (1.692)	0.0313 (0.0019)	-4418	2768
Uttar Pradesh (UP)	96.652 (1.212)	0.0208 (0.0010)	-5751	4069
Assam (AS)	42.663 (2.026)	0.0508 (0.0017)	-1282	2437
Rajasthan (RJ)	167.942 (0.002)	-0.0106 (0.1257)	-5843	2143
Panel B–Ownership	Fixed Costs (γ_0)	Curvature (γ_2)	Llk	# Obs.
Public-Private	30.655 (1.121)	0.0103 (0.0017)	-8166	5986
Private	66.660 (0.343)	0.0355 (0.0008)	-23205	56092

Note: This tables presents estimates of the dynamic parameters across states and ownership codes pooled over 10 industry codes. Standard errors are in parenthesis. Results evaluated at 1,000 US Dollars in 2005 constant prices.

Figure 7: Estimated Land Aggregation Costs across State



Note: This figure plots the fitted values of total land aggregation costs against the dollar value paid for a land transaction across different states. The 45° is the case of no land frictions. The data is from ASI [1999-2015].

6.2.1 Results across States

As can be seen from Panel A in Table 8, the fixed costs of land addition by manufacturing firms vary significantly across states. Estimating the land aggregation costs parameters separately across states is necessary given the heterogeneity in land markets in land laws and fragmentation rates across states. It also highlights the different land friction environments new manufacturing firms may face in different locations. The fixed costs (γ_0) are estimated to be as low as \$21,934 in the state of Gujarat and as high as \$167,942 in the state of Rajasthan (dollar values are in 2005 constant prices). In Gujarat, estimated fixed costs are 3.5% of the mean land addition in the state (66.7% of median land addition). In states with higher estimated fixed costs like Uttar Pradesh and Rajasthan, fixed costs are 25% and 32%, respectively of the mean land addition in the state. It is expected that Gujarat would have the lowest estimated fixed costs as it is considered the gold standard of land markets in India. See next subsection to see how estimated land aggregation costs parameters correlate with various other measures of land frictions in India.

Across states, the curvature parameter (γ_2) of land addition also varies significantly. It ranges from 0.012 in the state of Karnataka to 0.058 in the state of Maharashtra. Even for the state of Karnataka, with relatively low estimated curvature parameter, convex curvature costs add significantly to the cost of large land additions. For instance, curvature costs add 17% extra costs over and above the dollar value paid for the 90th percentile land addition in Karnataka. In Assam, with large estimated curvature parameter 0.0508, curvature costs add 80% extra costs over and above the dollar value for the 90th percentile land addition. In Maharashtra, with largest estimated curvature parameter, curvature costs add 119% extra costs over and above the dollar value for the 90th percentile land addition.

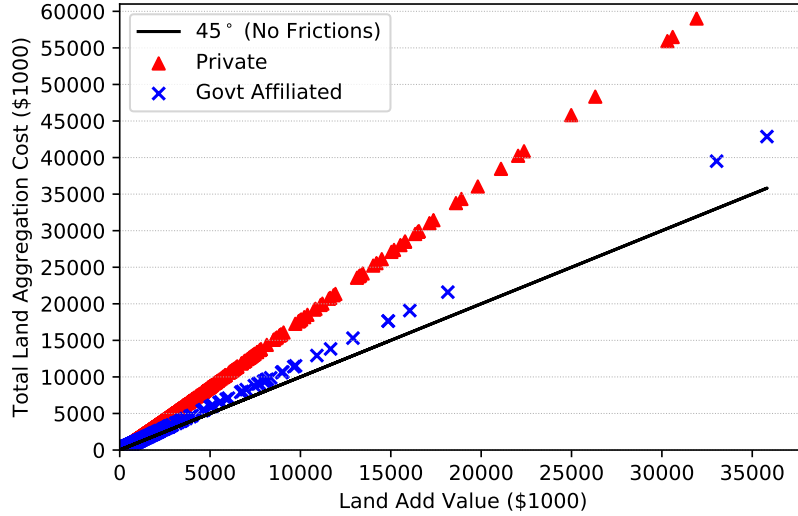
Figure 7 plots the fitted values of total land aggregation costs against the dollar value paid for a land transaction across different states. The black line is the 45° line, the case of no land frictions. As can be seen from the figure, for all states, the land aggregation costs are convex and above the 45° line. The total land aggregation costs are highest for firms in Maharashtra, Gujarat, and Tamil Nadu. This comes from the fact that the estimated convexity parameter is high in these states.

6.2.2 Results across Ownership

Across ownership codes, the estimated costs of land addition also vary significantly. The results in Panel B of Table 8 are presented are for privately held firms and firms that are jointly held by the government and the private sector (public-private). The results are not estimated for firms solely held by government due to small sample in that case. Estimating the land aggregation costs parameters separately across ownerships is necessary for two reasons. One, it highlights the discrepancy in land market frictions faced by private and government-affiliated firms. Second, we can consider the government-affiliated firms as a benchmark case as a comparison for a world with lower land frictions. The fixed costs are estimated to be \$30,665 for public-private firms. The fixed costs are estimated to be \$66,660 for private firms, twice as high as public-private firms. For public-private firms, estimated fixed costs are 2.5% of the mean land addition. For private firms, estimated fixed costs are 19% of the mean land addition.

The curvature parameter is estimated to be 0.01 for public-private firms. The curvature

Figure 8: Estimated Land Aggregation Costs across Ownerships



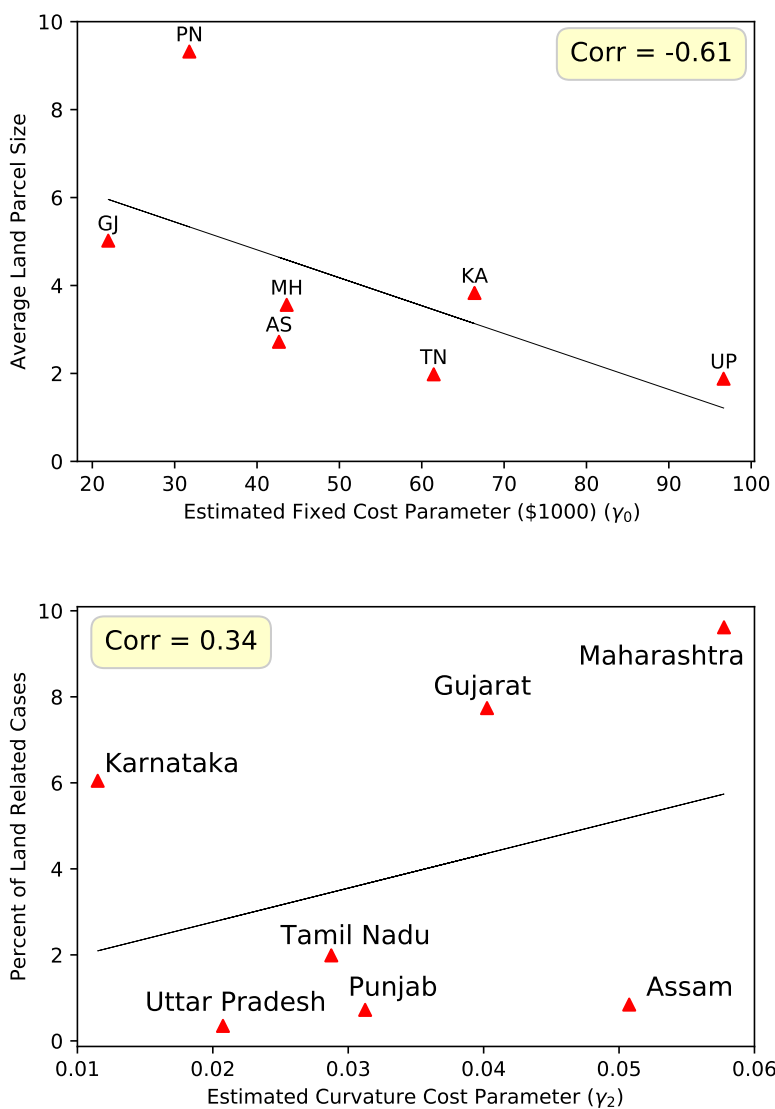
Note: This figure plots the fitted values of total land aggregation costs against the dollar value paid for a land transaction across ownerships. The 45° is the case of no land frictions. The data is from ASI [1999-2015].

parameter is estimated to be 0.036 for private firms, three times as high as public-private firms. Curvature costs add 16% extra costs for the 90th percentile land addition for public-private firms. Meanwhile, curvature costs add 60% extra costs for the 90th percentile land addition for private firms. Figure 8 plots the fitted values of total land aggregation costs against the dollar value paid for a land transaction across ownerships. The black line is the 45° line, the case of no land frictions. As can be seen from the figure, for both ownerships, the land aggregation costs are convex and above the 45° line. However, the total land aggregation costs faced by private firms are much higher and discrepancy between the costs increase as the dollar value of land input increases.

6.3 Estimated Parameters and Corroborating Evidence

This section provides corroborating evidence that estimated land aggregation costs from the model are correlated with some observed land market friction indicators. First, this paper corroborates the estimated fixed costs across states against the average land parcel size in a state as a measure for fragmentation. The possible role of land fragmentation in increasing the costs of land aggregation has been highlighted in this paper above. As can be seen from

Figure 9: Estimated Land Cost Parameters and Observed Land Market Frictions



Note: This figure presents plots the estimated land aggregation cost parameters and observed land market frictions across states. The top panel plots the average land parcel size against the estimated fixed costs in \$1,000 constant prices. The bottom panel plots the percent of land related civil court cases in 2015 against the estimated curvature costs. State of Rajasthan is not presented in these figures because its convex parameter is not precisely estimated. Correlation results do not change when Rajasthan is included in the figures. The data on manufacturing establishments is from ASI. The data on average land parcel size is from Agricultural Census 2005. The data on land court cases is self-collected from National Judicial Data Grid.

the top panel in Figure 9, the higher the average land parcel size, the lower the estimated fixed costs in the state. The correlation is -0.61 .²⁵ Second, this paper corroborates the estimated curvature parameter from the model against the observed land market frictions of land fragmentation and percent of land related civil court cases. As mentioned in the paper above, another measure that captures the increased costs from negotiations with large number of land holders and can proxy as for the effect of small average parcel size is the percent of land related court cases out of all civil cases. Using the data from 2015 across states, this paper finds that the increases in the percent of land related court cases in a state, increases the estimated land curvature costs (see bottom panel of Figure 9). The correlation is estimated to be 0.34 .²⁶

7 Policy Experiments

In this section, the paper uses the estimated parameters of the land aggregation cost structure to simulate counterfactual policy experiments. This is one of the benefits of estimating a structural model since it provides underlying primitives and allows for different policy experiments. Using the estimated parameters, I conduct policy experiments to study the impact of government policies that reduce land market frictions and the effect of the new eminent domain law amendment on manufacturing in India. In particular, the paper studies the impact of these policies on lifetime producer profits as measured by net present value of producer profits. The policy evaluation I consider are:

1. Proposed government policy of land-pooling
2. Effect of the new eminent domain restrictions (2015)

To run each of these experiments, I simulate firms' land adjustment choices along 9000 paths each of length 25, thus simulating 25 years ahead. One caveat to note: policy evaluation

²⁵State of Rajasthan is not presented in these figures because its convex parameter is not precisely estimated. Correlation results do not change when Rajasthan is included in the figures.

²⁶In addition, the late repeal of the land ceiling law (Urban Land Ceiling and Regulation Act (ULCRA)) is also an indicator of lower availability of larger land lots. In fact, this paper finds that the mean estimated curvature parameter is 0.054 for the states that repealed ULCRA later (post 2008) while the mean estimated curvature parameter is 0.027 for the states that repealed ULCRA before 2003.

calculations do not account for benefits of land frictions and consumer welfare.

7.1 Effect of Eminent Domain Law Amendment

The recent eminent domain amendment makes land aggregation difficult for the government and also reduces their scope of eminent domain use. To study the effect of the new eminent domain restrictions on firms that are affiliated with the government, I proceed by simulating firm paths for government-affiliated firms under land aggregation parameters of private firms. I compare firms with same initial productivity level across these two sets of land parameters (government-affiliated and private) at different productivity levels.

Table 9 provides results presents estimates of the total producer profits for government-affiliated firms under two sets of parameters in net present value terms across different productivity levels. Producer profits are means over different land input values. Column 1 gives the total producer profits for government-affiliated firms for 10 industries under the estimated land cost structure of government affiliated firms. The producer lifetime profits are evaluated for firms starting with productivity at 10th, 25th, 50th, 75th, 95th and 99th percentile. Column 2 gives gives the total producer profits for government affiliated firms for 10 industries under the estimated land cost structure of private firms. Column 3 provides the loss in total lifetime producer profit of new the eminent domain restrictions where the government-affiliated firms face the same land aggregation costs as private firms. We see the loss in total lifetime producer profit is between \$1.0M for the low productivity firms up to \$6.8M for the firms with starting productivity of 99th percentile. I terms of percentage change in loss in total lifetime producer profit, lowest productivity firms lose 1.1% in lifetime profits while highest productivity firms lose 4.8% in lifetime profits.

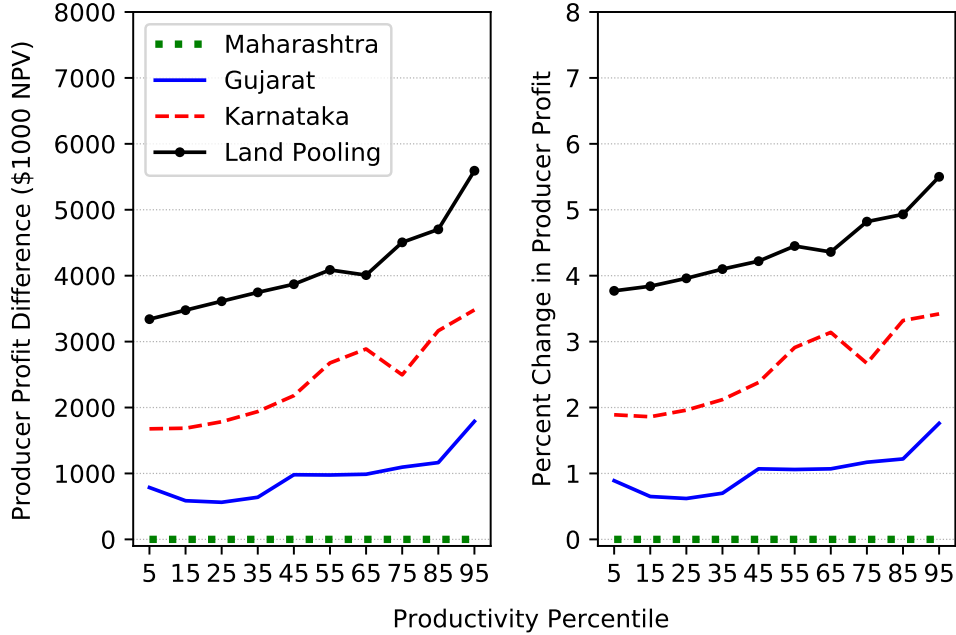
From the estimated parameters, it can be seen that government-affiliated first have been subject to smaller land frictions than private ones. Removing the eminent domain channels brings everyone brings everyone to the same playing level field of high land aggregation frictions, reducing lifetime producer profits by up to 4.8% for the most productive firms.

Table 9: Effect of Eminent Domain Law Restrictions

Start Prod. Percentile	Govt. Aff. Profit	Private Profit	Δ	$\Delta\%$
10th	94,566	93,554	-1012	-1.07%
25th	102,131	100,398	-1733	-1.70%
50th	120,514	117,923	-2591	-2.15%
75th	130,796	127,641	-3155	-2.41%
95th	137,020	131,936	-5083	-3.71%
99th	141,950	135,136	-6814	-4.80%

Note: This tables presents estimates of the total producer profits for government-affiliated firms under two sets of parameters in net present value terms across different productivity levels. Producer profits are means over different land input values. Results evaluated at 1,000 US Dollars in 2005 constant prices. NPV: net present value.

Figure 10: Effect of Land-Pooling Policy for Firms in Maharashtra



Note: This figure plots the difference in mean total producer profits for Maharashtra firms against the land friction environment of Gujarat and Karnataka in net present value terms across different productivity levels. The data on manufacturing establishments is from ASI. Results evaluated at 1,000 US Dollars in 2005 constant prices.

7.2 Effect of Government Land-Pooling Policies

To study the effect of policies that encourage land aggregation and proposed government policy of land-pooling where government acts as an intermediary to aggregate land, I proceed by simulating firm paths under three sets of curvature parameters. First, I set the cost of land aggregation costs structure to that of Gujarat, state with lowest estimated sunk costs. Second, I set the cost of land aggregation costs structure to that of Karnataka, state with lowest estimated convex costs. Third, I set the cost of land aggregation costs structure to the case on zero land aggregation costs which would happen in the case of government land-pooling policy. I compare firms with same initial productivity level across these three sets of land parameters and compare benefits against firms located in Maharashtra that have Maharashtra's land aggregation cost structure. I compare across different starting productivity levels of firms.

Figure 10 provides results presents estimates of the total producer profits for Maharashtra

firms under three sets of parameters in net present value terms across different productivity levels. Producer profits are means over different land input values. The panel on the left provides the gain in total lifetime producer profit of Maharashtra firms under the land aggregation costs of Gujarat, Karnataka, and land-pooling (no aggregation costs). The panel on the right provides the gain in total lifetime producer profit in percentage terms. As can be seen from the figure, the gain in total lifetime producer profit is between \$3.2M (3.9%) for the low productivity firms (5th percentile) up to \$5.8M (5.6%) for the firms with starting productivity of 95th percentile from land-pooling policies. Lower convex costs from the cost parameters of Karnataka, increase total lifetime producer profit by \$3.5M (3.5%) or the firms with starting productivity of 95th percentile from land-pooling policies. Lower sunk costs from the cost parameters of Gujarat, increase total lifetime producer profit by \$1.9M (1.9%) or the firms with starting productivity of 95th percentile from land pooling-policies.

8 Conclusion

Manufacturing firms in developing countries are small. This paper argues that land market frictions contribute to this. This paper estimates the land aggregation cost structure for manufacturing incumbents in India. Exploiting the regional and ownership variation in land market frictions and firm land adjustment behavior, this paper quantifies the effects of land market frictions on the Indian manufacturing sector. I find that firm land adjustment strategies differ significantly across states and ownerships. I also find that land aggregation frictions vary significantly across different regions in the country, adding significant fixed and convex costs to land expansion over and above the dollar value paid. In addition, land costs are three times higher for private establishments. The paper also shows that land is a significant input into the production of manufacturing establishments and estimates land elasticity while accounting for endogeneity concerns. Using the estimated parameters, I calculate that land-pooling policies increase lifetime producer profits by up to 5.5%. I also estimate that the recent amendment restricting government's eminent domain powers lower lifetime producer profits by up to 4.8%. Land market frictions and their effect on manufacturing in India have long been discussed by the Indian government, consulting firms, and manufacturers. This

paper quantifies the significant effects of land frictions on manufacturing in India.

References

- Adamopoulos, T. and D. Restuccia (2014). The size distribution of farms and international productivity differences. *American Economic Review* 104(6), 1667–97.
- Banerjee, A. V. and E. Duflo (2005). Growth theory through the lens of development economics. *Handbook of economic growth* 1, 473–552.
- Bau, N. and A. Matray (2019). Misallocation and capital market integration: Evidence from india. working paper.
- Bertaud, A. and S. Malpezzi (2003). The spatial distribution of population in 48 world cities: Implications for economies in transition. *Center for urban land economics research, University of Wisconsin* 32(1), 54–55.
- Besley, T. and R. Burgess (2004). Can labor regulation hinder economic performance? evidence from india. *The Quarterly journal of economics* 119(1), 91–134.
- Bloom, N., B. Eifert, A. Mahajan, D. McKenzie, and J. Roberts (2013). Does management matter? evidence from india. *The Quarterly Journal of Economics* 128(1), 1–51.
- Boehm, J. and E. Oberfield (2018). Misallocation in the market for inputs: Enforcement and the organization of production. Technical report, National Bureau of Economic Research.
- Butters, F. F. (2015). Runaway use of eminent domain and the effect on the inner city runaway use of eminent domain and the effect on the inner city. Technical report, American Institute of Architects.
- Caballero, R. J. (1999). Aggregate investment. *Handbook of macroeconomics* 1, 813–862.
- Chakravorty, S. (2013). A new price regime: Land markets in urban and rural india. *Economic and Political Weekly*, 45–54.
- Chand, R., P. L. Prasanna, and A. Singh (2011). Farm size and productivity: Understanding the strengths of smallholders and improving their livelihoods. *Economic and Political Weekly* 46(26), 5–11.

- Chen, C., D. Restuccia, and R. Santaeuilàlia-Llopis (2017). The effects of land markets on resource allocation and agricultural productivity. Technical report, National Bureau of Economic Research.
- Collard-Wexler, A. and J. De Loecker (2016). Production function estimation with measurement error in inputs. Technical report, National Bureau of Economic Research.
- CSIS (2016, July). Wadhvani-nathan breakthrough index: Industrial land policy. *Center for Strategic and International Studies* 1(1).
- Deininger, K. and G. Feder (2001). Land institutions and land markets. *Handbook of agricultural economics* 1, 287–331.
- Demetriou, D., J. Stillwell, and L. See (2012). An integrated planning and decision support system (ipdss) for land consolidation: Theoretical framework and application of the land-redistribution modules. *Environment and Planning B: Planning and Design* 39(4), 609–628.
- Deshpande, R. (2003). Current land policy issues in india. *Land Reform, Land Settlement and Cooperative*, 155–174.
- Ding, C. (2007). Policy and praxis of land acquisition in china. *Land use policy* 24(1), 1–13.
- Duranton, G., E. Ghani, A. G. Goswami, and W. Kerr (2015). *The misallocation of land and other factors of production in India*. The World Bank.
- Dutta, M. (2009). Nokia sez: Public price of success. *Economic and Political Weekly*, 23–25.
- Economist, T. (2013, September). This land is whose land?
- Feder, G. and D. Feeny (1991). Land tenure and property rights: Theory and implications for development policy. *The World Bank Economic Review* 5(1), 135–153.
- Ghatak, M. and P. Ghosh (2011). The land acquisition bill: a critique and a proposal. *Economic and Political Weekly* 46(41), 65–72.

- Ghatak, M., S. Mitra, D. Mookherjee, and A. Nath (2013). Land acquisition and compensation: What really happened in singur? *Economic and Political Weekly*, 32–44.
- Ghatak, M. and D. Mookherjee (2014). Land acquisition for industrialization and compensation of displaced farmers. *Journal of Development Economics* 110, 303–312.
- Glaeser, E. (2014). Land use restrictions and other barriers to growth. *Cato Institute*.
- Glaeser, E. L. and B. A. Ward (2009). The causes and consequences of land use regulation: Evidence from greater boston. *Journal of Urban Economics* 65(3), 265–278.
- Govindarajan, V. and G. Bagla (2015, September). Understanding the rise of manufacturing in india. *Harvard Business Review*.
- Heller, M. A. (1998). The tragedy of the anticommons: property in the transition from marx to markets. *Harvard law review*, 621–688.
- Herkenhoff, K. F., L. E. Ohanian, and E. C. Prescott (2018). Tarnishing the golden and empire states: Land-use restrictions and the us economic slowdown. *Journal of Monetary Economics* 93, 89–109.
- Hsieh, C.-T. and P. J. Klenow (2009). Misallocation and manufacturing tfp in china and india. *The Quarterly journal of economics* 124(4), 1403–1448.
- Hsieh, C.-T. and B. A. Olken (2014). The missing” missing middle”. *Journal of Economic Perspectives* 28(3), 89–108.
- Jha, R., H. K. Nagarajan, S. Prasanna, et al. (2005). Land fragmentation and its implications for productivity: Evidence from southern india.
- Levinsohn, J. and A. Petrin (2003). Estimating production functions using inputs to control for unobservables. *The review of economic studies* 70(2), 317–341.
- Lusho, S., D. Papa, et al. (1998). Land fragmentation and consolidation in albania.
- MacDonald, J. M., P. Korb, and R. A. Hoppe (2013). Farm size and the organization of us crop farming. Technical report.

- Maitreesh Ghatak, P. G. and D. Mookherjee (2013, November). Reforming india's land policy. *Yojana*.
- Mamidi, P. K. (2012). Negotiating out of holdouts in land aggregation in india: small town lawyers, contingent contracts, social norms, and auctions. *HLS Program on the Legal Profession Research Paper* (2013-1).
- Manjunatha, A., A. R. Anik, S. Speelman, and E. Nuppenau (2013). Impact of land fragmentation, farm size, land ownership and crop diversity on profit and efficiency of irrigated farms in india. *Land Use Policy* 31, 397–405.
- Miceli, T. J. and K. Segerson (2007). A bargaining model of holdouts and takings. *American Law and Economics Review* 9(1), 160–174.
- Niroula, G. S. and G. B. Thapa (2005). Impacts and causes of land fragmentation, and lessons learned from land consolidation in south asia. *Land use policy* 22(4), 358–372.
- Nordhaus, W. D., R. N. Stavins, and M. L. Weitzman (1992). Lethal model 2: the limits to growth revisited. *Brookings papers on economic activity* 1992(2), 1–59.
- Oldenburg, P. (1990). Land consolidation as land reform, in india. *World Development* 18(2), 183–195.
- Olley, G. S. and A. Pakes (1996). The dynamics of productivity in the telecommunications equipment industry. *Econometrica: Journal of the Econometric Society*, 1263–1297.
- Owen, C. J. (1990). Microgeographic decisions in an industrial plant location: The fort wayne general motors case. *Economic Development Quarterly* 4(2), 137–143.
- Parikh, K. S. and H. K. Nagarajan (2004). *How Important is Land Consolidation?: Land Fragmentation and Implications for Productivity: Case Study of Village Nelpathur in Tamil Nadu*. National bank for agriculture and rural development.
- Restuccia, D. and R. Santaaulalia-Llopis (2017). Land misallocation and productivity. Technical report, National Bureau of Economic Research.

- Rust, J. (1987). Optimal replacement of gmc bus engines: An empirical model of harold zurcher. *Econometrica: Journal of the Econometric Society*, 999–1033.
- Ryan, S. P. (2012). The costs of environmental regulation in a concentrated industry. *Econometrica* 80(3), 1019–1061.
- Valentinyi, A. and B. Herrendorf (2008). Measuring factor income shares at the sectoral level. *Review of Economic Dynamics* 11(4), 820–835.

Appendices

A Background to Land Market Frictions in India

A.1 Case Study of Land Acquisition in Car Manufacturing Industry

Consider a typical case of land aggregation for an automobile plant in the U.S. For its Fort Wayne plant in Indiana, GM acquired 937 acres of land from 29 owners in a period of two months in 1984 (Owen, 1990). In the U.S., there has been only one case where eminent domain was used to acquire land in the automobile industry. For a GM plant setup in Poletown (suburban Detroit) in Michigan in 1981, the local government acquired 465 acres from 1447 households and businesses (Butters, 2015). Contrast that with the land acquisition process for the automobile industry in India. Consider the case of the Tata Nano plant where the government of the Indian state of West Bengal used eminent domain to aggregate 997 acres of land. It did so by aggregating over 13,970 parcels and provided compensation to around 12,000 landholders (Ghatak et al., 2013). Use of eminent domain for large scale manufacturing is common in India. Of the 28 automobile plants setup in India since 1980, at least 79% have been developed on land aggregated using eminent domain. However, eminent domain is fraught with controversy and on average, it can take up to 2 years to aggregate land using eminent domain in India.

A.2 Fragmentation and Land Policy Issues in India

Land market frictions in India arise due to increased land fragmentation over time, ineffective land related policies, and thin land markets. Historically in India, land bequests occurred from father to all children, splitting a land parcel into multiple parcels (Jha et al., 2005). This is unlike the American or British inheritance system where land was passed on to the eldest son.²⁷ In addition, after independence from the British in 1947, the Indian government transferred land from few landlords to many farmers (Deshpande, 2003). While these efforts met goal of equity in land holdings to a certain extent, they also increased the land parcel

²⁷Historically, the French followed an inheritance system like Indians and land parcels sizes in France were much smaller than that in Britain (Lusho et al., 1998).

fragmentation in the country (Jha et al., 2005). The average parcel size decreased from 5.7 acres in 1971 to 2.8 acres 2011. Given the average parcel size of 2.8 acres, a firm may have to, on an average, aggregate over 172 parcels to setup a manufacturing plant for 500 acres.²⁸ Land fragmentation not only reduces the size of each parcel, it also makes parcel shapes irregular and results in loss of land that gets absorbed in boundaries (Demetriou et al., 2012). See Figure 1 to see what the land parcel shapes and size look like in an average village. Additionally, due to several socio-economic reasons, land holders are less willing to sell land in India. Holding land is considered a symbol of higher social status and paucity of other safe assets makes holding land particularly attractive (Niroula and Thapa, 2005).²⁹ Maitreesh Ghatak and Mookherjee (2013) argue that poor land records make it harder to transfer land ownership, while lack of brokerage services and limited flow of information about buying and selling opportunities create frictions in the land markets.

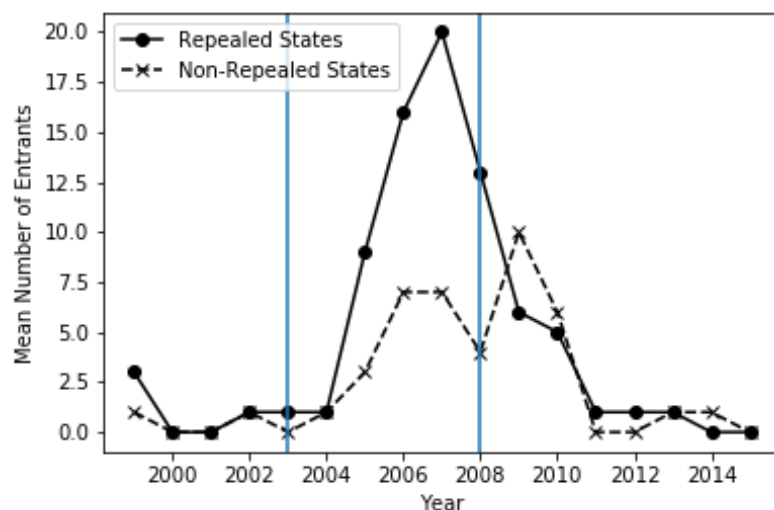
Aggregating large and contiguous parcels of land for manufacturing purposes is also difficult due to policy reasons. Laws in most states in India prohibit the sale of agricultural land to anyone but agriculturalists i.e. people already owning some agricultural land (Deshpande, 2003). There are also severe leasing restrictions for land leases for manufacturing purposes (CSIS, 2016). In the 1970s, India introduced land ceiling laws that prohibited holding unused land above a certain threshold, preventing agents in the economy to aggregate land. In addition, strict tenancy laws in favor of tenants lead to concealment of ownership status adding to the frictions in the land market (Deshpande, 2003). Furthermore, land transaction taxes are also very high in India. This results in underreporting of real sale values and thinner land markets. The fragmentation, socio-economic issues and ill-effects from land policies compound and make aggregation of land parcels difficult. This becomes an issue for economic activities that require large inputs of land such as large-scale agriculture, infrastructure, and manufacturing. The focus of this paper is on large scale manufacturing.

In addition to the land market frictions that induce firms to hold land without building and a land adjustment strategy based on bite by bite land addition, land policies also affect the manufacturing sector. Consider the land ceiling law ULCRA (1976) which imposed a

²⁸Contrast this with land acquisition in China where land is state owned and leased out to industries circumventing bargaining issues associated with fragmentation (Ding, 2007).

²⁹See (Chakravorty, 2013) for thin and inactive land markets, especially in rural India.

Figure A1: Mean Number of Entrants across ULCRA Repeal and Non-Repeal States



Note: This figure mean number of manufacturing entrants across ULCRA (land ceiling law) repeal and non-repeal states [1999-2014]. The first vertical line in 2003 represents the first stage of repeal. Vertical line in 2008 represents the later stage of repeal. The data is from ASI and self collected.

ceiling on ownership and possession of vacant land in urban areas. Even though the purpose of the law was to increase the supply of urban land, the result was a restriction on supply and increased land prices since such land was held up in lengthy legal battles (Bertaud and Malpezzi, 2003). In 2003 some states has repealed the land ceiling law and it had an immediate effect on the entry by manufacturing establishments in those states. See Figure A1 for increase in mean number of large entrants (100 employees or more at entry date) in the states that repealed the law compared to states that did not. In 2008, more states repealed the land ceiling law.

B Data Methods

B.1 Data Cleaning Exercises

The industry classification in the ASI data is given by National Industrial Classification (NIC) codes which are closely related to SIC codes. The NIC codes changed twice during the sample in years 2004 and 2008. A direct correspondence across the three NIC codes does not exist. Thus instead of attempting to match NIC coded across industries, this paper selected firms that have at least one NIC-2008 classification. It then applied this NIC-2008 classification to all available years for that firm. In addition, land and other capital input data is also cleaned using the redundant questions asked by ASI. This paper uses the procedure that is followed by the U.S. Census Bureau which makes sure that the final value is a sum (or difference) of additions (or deductions). Thus, for land and capital input, I take the opening value of land and capital stock and follow the additions and subtractions as shown in Figure 5.

B.2 Deflators

The data on manufacturing deflators known as Wholesale Price Index (WPI) comes from the Office of the Economic Advisor of India. The NIC classification for the deflators does not match one-to one with the industry codes from ASI dataset. To overcome this issue, I hand match the two digit ASI industry code level to the closest matching industry in WPI data. For material item codes with no close matches, I deflate using the aggregate manufacturing deflator. Since capital stock data is disaggregated, I deflate the plant and machinery equipment and transport equipment capital stock with matching WPI deflators. The remaining capital stock is deflated using the RBI's Gross Domestic Capital Stock Formation (GDCS) deflator. A land price index by RBI is available for residential prices in 10 major cities in India, based on mortgage data. The extent of correlation between residential, industrial and agricultural land price indices is not obvious. In the absence of any land price data on agricultural and industrial land in India, I construct deflated land value measure in three district ways. I do robustness checks to assure that my results do not vary drastically based on the method of deflation. First, I deflate land value using the GDCS deflator. Second, I

Figure A2: ASI Form for Fixed Capital: Sample

DSL No PSL No

Block C: FIXED ASSETS													
Sl. No.	Type of Assets	Gross value (Rs.)					Depreciation (Rs.)				Net value (Rs.)		
		Opening as on ----	Addition during the year		Deduction & adjustment during the year	Closing as on ---- (cols. 3+4+5-6)	Up to year beginning	Provi- ded during the year	Adjustment for sold/ discarded during the year	Up to year end (cols. 8+9 -10)	Opening as on	Closing as on	
(1)	(2)	(3)	Due to revaluation	Actual additions							(6)	(7)	(8)
1.	Land												
2.	Building												
3.	Plant & Machinery												
4.	Transport equipment												
5.	Computer equipment including software												
6.	Pollution control equipment												
7.	Others												
8.	Sub-total (items 2 to 7)												
9.	Capital work in progress												
10.	Total (items 1+8+9)												

use the RBI residential price deflator for states in which the 10 major cities are in.

In addition, deflating the value of land is done in two ways so that proper base year for delation can be established. The challenge is that for firms that entered before 1998 (35% of firms), I cannot see if the price of land is at original land price value or has been reevaluated at some point of time. Since, the ASI guidelines recommend not reevaluating the land input and I see less than 1% of firm reevaluating land in the data, I assume that the price shown is at original land price value of the date of entry. This assumption does not account for the fact that if additions made post the entry year, the added value is marked at sale value of the year of addition.

B.3 Agricultural Census Data

I have data on Agricultural Census of 2000, 2005, and 2010. The analysis in this paper is at state level. The Agricultural Census provides detailed information on discrete distribution of location area divided into 10 lot size bins indexed by q . Create two indices of fragmentation

f_{jt}^1, f_{jt}^2 for location j at time t :

$$f_{jt}^1 = \sum_{q=1}^{10} s_{qjt} Q_{qjt} \qquad f_{jt}^2 = \sum_{q=1}^{10} s_{qjt} Q_{qjt} a_{qjt}$$

s_{qjt} is the share of total location j 's land in lot size bin q . Q_{qjt} is the midpoint area of lot size bins q and a_{qjt} is the area in lot size bin q . f_{jt}^1 is the number index and f_{jt}^2 is the area index. Index f_{jt}^2 puts more weight on bigger states that have higher area in larger lots. Table [A1](#) provides summary statistics on land fragmentation over time across states in India.

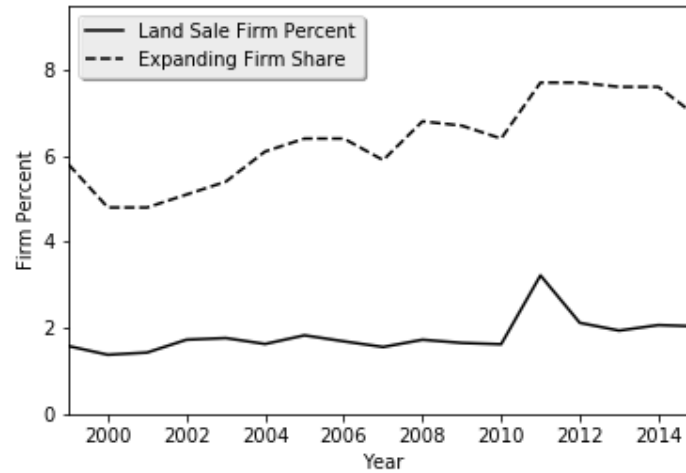
Table A1: Summary Statistics: Land Fragmentation over Time

Year	Average Parcel Size (acres)		Number Index		Area Index		N
	Mean	S.D	Mean	S.D	Mean	S.D	
2000	1.80	1.47	1.94	1.14	4.45	2.48	26
2005	1.62	1.35	1.74	1.26	4.40	2.59	29
2010	1.62	1.25	1.75	1.23	4.08	2.31	26

Note: This tables provides summary statistics on land fragmentation over time across states in India. Data is from Agricultural Census of India 2000, 2005, and 2010.

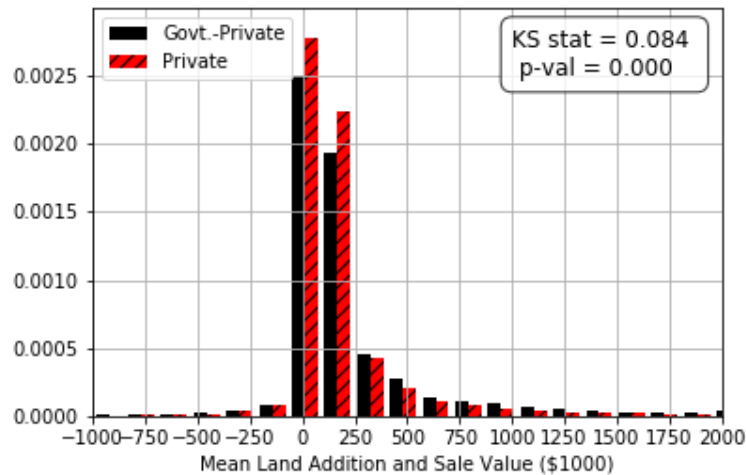
C Descriptive Evidence: Land Bite Strategy and Land Frictions

Figure A3: Land Adjustment in Cross-Section



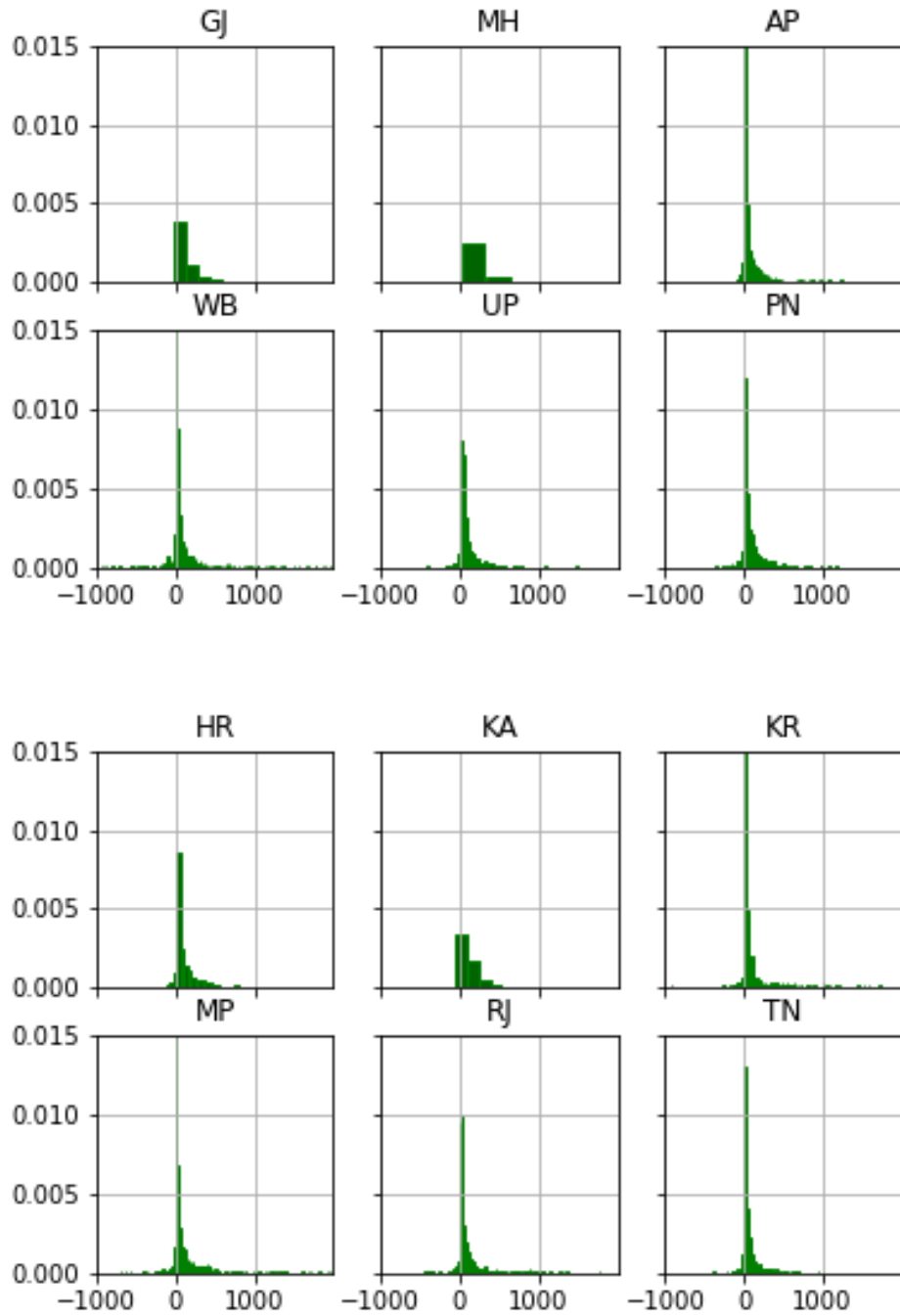
Note: This figure presents the share of establishment adjusting land in a given cross section year [1999-2015]. The data is from ASI.

Figure A4: Density of Land Adjustment across Ownership Status



Note: This figure presents the land adjustment density of firms varied across ownership status [1999-2015]. Establishments are either fully private owned or jointly owned by government and private parties. Values are in 2005 constant thousand USD. The Kolmogorov-Smirnov test shows that the two empirical distributions are different in statistically significant manner rejecting the null hypothesis of same distribution by p-value of 0.000. The figure is truncated on both sides for clarity. The data is from ASI.

Figure A5: Density of Land Adjustment across States



Note: This figure presents the land adjustment density of firms across states [1999-2015]. The figure presents data from 12 states with most manufacturing. State index:- GJ: Gujarat, MH: Maharashtra, AP: Andhra Pradesh, WB: West Bengal, UP: Uttar Pradesh, PN: Punjab, HR: Haryana, KA: Karnataka, KR: Kerala, MP: Madhya Pradesh, RJ: Rajasthan, TN: Tamil Nadu. Values are in 2005 constant thousand USD. The figure is truncated on both sides for clarity. The data is from ASI.

D Production Function Estimation: Productivity Estimates

Table A2: Productivity Residual Estimates

Industry (NIC Code)	Count	Mean	St. Dev.
Food Products (10)	19026	12.725	1.497
Textile (13)	14983	12.036	1.139
Non-Metallic Mineral (23)	13752	10.551	1.463
Chemical Products	10114	12.457	1.617
Basic Metals (24)	8165	12.207	1.383
Machinery & Equipment (28)	8061	12.936	1.536
Wearing Apparel (14)	6114	10.634	1.123
Fabricated metals (25)	6628	12.023	1.372
Vehicles (29)	6631	11.741	1.253
Electrical Equipment (27)	6265	13.454	1.610

Note: This tables presents the residual productivity estimates from Levinsohn and Petrin (2003) estimation on Indian manufacturing establishment data (1999-2015) using both land and capital as state variables.