Land Market Frictions and Differential Manufacturing and Services Growth: Evidence from India's Structural Transformation *

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Abstract

We study how land market frictions differentially affect the growth of manufacturing plants and services sector firms in India. To check for the impact of land market frictions, we ask whether firms in industries that require relatively more land perform disproportionately worse in states with more land fragmentation. Using output and employment as outcomes, we find that it is true for manufacturing plants in panel as well as cross-section specification. We do not find any such effect for services sector firms using a cross-section specification. We show that this can happen due to low land requirement of service sector firms. We further explore the results of manufacturing plants. The effect is larger among younger plants, among plants in industries requiring more land and among privately owned plants. We also find effects on labor productivity and plant entry. Moreover, we show that this effect of fragmentation is higher in states with more land disputes and lower land rental activity. Our estimates are robust to multiple ways in which we measure land requirement of industries. We also show that our results are unlikely to be driven by any alternative explanations.

JEL Classification: O14, R52, L60, L80

Keywords: Land Frictions, Manufacturing, Services, Structural Transformation, India

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1 Introduction

India's structural transformation experience is characterized by the coexistence of a manufacturing sector with muted growth and a services sector with spectacular growth. The share of services sector in value added increased from 39.3% in 1991 to 54.7% in 2012 while the share of manufacturing sector remained stagnant at around 30% during the same period.[1] As a result, almost all of the 15% decline in the share of agriculture in value added has been accounted for by a rise in services sector share. This stands in contrast to the typical structural transformation experience of a developed country which involves a reallocation of activities from agriculture to manufacturing first and *then* from manufacturing to services (Herrendorf, Rogerson and Valentinyi, 2014). The experience has remained similar for employment shares also. Scholars have related this experience to the phenomenon of "premature deindustrialisation" pointed out by Rodrik (2016) and further exemplified by Amirapu and Subramanian (2015) and Lamba and Subramanian (2020).

The standard supply side theory of structural transformation predicts that labor reallocates to the sector with lower TFP growth (Huneeus and Rogerson, 2020; Ngai and Pissarides, 2007). This can help in explaining the evolution of sectoral trends of developed countries given that their sectoral TFP growth was the highest for agriculture and the lowest for services. However, in India, services sector also exhibits the highest TFP growth among the three sectors (Serrano-Quintero, 2021; Verma, 2012). This can make it difficult to explain India's evolution of sectoral shares using standard supply-side theories of structural transformation.[2] Given this difficulty, the literature has resorted to other explanations: lop-sided skill development (Serrano-Quintero, 2021), rise of modern services (Eichengreen and Gupta, 2011), interaction of labor laws with input quota regulations (Gupta, 2009), etc. We contribute to this literature by drawing attention to a complementary process of a market friction in India which happens to adversely affect the growth of manufacturing plants more compared to services firms: land market

[1]Estimated from Groningen Growth and Development Centre (GGDC) 10-sector database.

[2]While Huneeus and Rogerson (2020) show that variation in agricultural productivity growth can explain observed variation in peak employment, India's manufacturing employment share has not peaked yet and hence is out of the sample. Moreover, their model shows that peak manufacturing employment share increases in services productivity growth, in line with the intuition laid out by Ngai and Pissarides (2007).

frictions.

Bolhuis, Rachapalli and Restuccia (2021) and Deininger, Jin and Nagarajan (2008) have shown that restrictions in land rental market can lead to misallocation of land within agriculture sector, which lowers agriculture productivity and possibly, slows down the movement of labor out of agriculture. However, there is very little evidence on how land market frictions *differentially* impact the growth of firms within manufacturing and services sectors. Our paper attempts to fill this gap in the literature.

It has been widely documented in popular media that land markets in India are rigid and thin (Khanna, 2021; Rajan, 2013). The act of transferring a parcel of land from one party to another is faced with many obstacles arising due to restrictions laid out by the government and for various socioeconomic reasons. Until recently, in almost all the states in India, there are legal restrictions on the voluntary transfer of land from agriculture to non-agriculturalists (Blakeslee et al., 2021). In addition, poor land records hinder the transaction of land when multiple owners claim the right to one piece of land (Roy and Swamy, 2022). While major economic activities were liberalised and privatised in 1991, the land market is one place where no concomitant reforms have been made (Burman, 2022). The two decades of high economic growth following 1991 creates natural pressure for shifting activities away from agriculture. However, given the rigidity of land markets, which restricts land from changing owners, land markets have become a "binding" constraint for growth of firms (Roy and Swamy, 2022).

In this paper, we argue that the impact of land market frictions on growth of industries differ based on the land requirement of industries. Plants in some industries like petroleum, automobile, etc. naturally operate on a larger scale and hence, require more land compared to those in industries like furniture, wearing apparels, etc. which can operate on a small scale and hence require less land. To the extent land requirement also differs across manufacturing and services sectors, land market frictions can adversely affect the growth of manufacturing sector plants disproportionately more compared to the services sector firms.[3]

Similar to the recent works of Sood (2022) and Pal, Roy Chowdhury and Saher (2022),

[3]Table 3 shows that land requirement of an average industry within manufacturing sector is more than 5 times that of an average industry within services sector. This is further demonstrated in Figure 6 which compares the distributions of land values of industries in manufacturing and services sectors.

we use land fragmentation in a state as a metric for measuring difficulty in acquiring land by firms. Land in India is highly fragmented compared to other countries and it varies across states and over time because of the state specific land ceilings imposed during the land ceiling legislations drive in the 1970s and the practice of land inheritance, which often splits up parcels among multiple children in one family. Purchasing an area of land requires acquiring multiple parcels in a state with more land fragmentation compared to a state with less land fragmentation. Because the above mentioned frictions make transaction for each parcel of land difficult, it will make acquisition of land more costly in a state with more fragmented land.

Our empirical strategy implements a stricter test to identify the impact of land market frictions on the outcome of firms. We ask whether firms in industries (2-digit ISIC level) that require relatively more land perform disproportionately worse compared to those in less land requiring industries, in states with more land fragmentation relative to those with less fragmented land. If the answer turns out to be yes, we take this as an evidence that land market frictions negatively affect performance of firms. This stricter test has the capacity of ruling out any alternative explanations based on unobservable variation at the level of state which can impact firm growth, but not necessarily along the dimension of land requirement of industries.[4]

We use panel data from Annual Survey of Industries (ASI) to evaluate this hypothesis for manufacturing sector plants. Using the above strategy, we find that land market frictions have negative and significant impact on output and employment of manufacturing plants. Our estimates from the panel specification suggest that the 5-year growth of output and employment for plants in industries with high land requirement (75^{th} percentile) *slows down* by 11.8 and 9.9 percentage points, respectively, compared to those in low land requiring industries (25^{th} percentile), as the state average land parcel size reduces from 75^{th} to 25^{th} percentile. Given that the average 5-year growth of output and employment is 34.5% and 9.6%, respectively, the effects that we find are sizeable. A similar negative and significant impact of land market frictions is found in the cross-section specification also.

[4] A similar empirical strategy has been used in the literature to identify the effects of financial development on industrial growth (Rajan and Zingales, 1998), impact of contract enforcement on organisation of production (Boehm and Oberfield, 2020) and impact of labor reforms on firm productivity (Dougherty, Frisancho and Krishna, 2014).

For services sector firms, given the paucity of panel or repeated cross-section data, we run a cross-section specification using micro-data from Service Sector in India Survey (NSS 2006-07). We fail to find any negative or significant impact of land market frictions on outcomes of services firms. The null result continues to hold when we try to capture the land requirement of services sector industries in various different ways, all of which exhibit significant effects for plants in manufacturing sector. We take this as a suggestive evidence that land market frictions impact the outcome of plants in manufacturing sector disproportionately more compared to those in services. To rationalise this contrast, we show two facts. First, land requirement of industries within services sector is very low compared to manufacturing sector: land requirement of an average industry within manufacturing sector is more than 5 times that of an average industry within services sector. At low levels of land requirement, fragmentation of land can become irrelevant for the growth of services sector firms. Second, employment size of a firm is less tied to land as a factor of production in services sector compared to manufacturing sector. A 1% increase in the value of land owned by a manufacturing plant is associated with 0.36% increase in the plant's employment while this number is 0.23% for a service sector firm. Given this flexibility, a service sector firm can adjust more along the margins of other inputs compared to a manufacturing plant.

We further explore the results of manufacturing plants using the panel specification. We show that this effect also holds for labor productivity (output per unit of labor) and also along the extensive margin (entry of manufacturing plants). Next, we study the heterogeneity of our main results with respect to three dimensions. First, we expect the land market frictions to affect younger firms more compared to older firms given that we expect older firms to have formed ties with the local neighbourhood as well as bureaucrats which may make land transactions relatively less burdensome for them. Next, we expect the frictions to affect plants in high land requiring industries more compared to plants in low land requiring industries, given that we expect cost of acquiring fragmented land to increase non-linearly with increase in transaction size. Finally, we expect privately owned plants to be affected more compared to publicly owned plants given that it can be relatively easier for the publicly owned plants to surpass the bureaucratic and political hassle in land acquisition process. Consistent with the expectations, we find similar evidences along all the above three dimensions.

To rule out alternative explanations related to labor or capital intensity of industries, we show that the magnitude of the impact of change in state level land fragmentation along the dimension of land requirement of industries is unaffected when we allow the impact to differ along labor or capital intensity of industries also. Similarly, to rule out alternative explanations related to factors that may change with state land fragmentation, we show that our main results are unaffected when allow the impact along the dimension of land requirement of industries to respond to changes in state level income per capita, literacy rates and share of agriculture in state level domestic product. On the other hand, we also show that the location of the entire sample of plants across industries is not systematically driven by the land fragmentation of states. Hence, it alleviates any concern related to endogenous location of plants across states. These results together strengthen the causal appeal of our empirical strategy.

For mechanism, we attempt to show that the impact of land fragmentation is actually due to the land market frictions described before. For this, we present two evidences. First, we show that the impact is higher (3 times and 4.6 times for output and employment, respectively) in states with higher age of pending cases in courts related to land disputes. This measure proxies for the intensity of poor land records related issues in a state. Second, we show that the impact is higher (1.73 times and 6.6 times for output and employment, respectively) in states with lower land rental market activity of agricultural households. Both lower land rental market activity and poor land records issue highlight higher land market frictions in a state, and therefore, they are convincing evidences to show that the effect of land fragmentation is actually being driven by land market frictions. Finally, we show that similar to output and employment, the value of land owned also grows slowly for plants in more land requiring industries relative to those in less land requiring industries as the state average land parcel size reduces. This is consistent with the hypothesis that the impact of land fragmentation on plant outcomes is due to the difficulty in acquisition of land.

We show that our main result is robust to alternative ways of measuring the land requirement of industries, including a completely exogenous (albeit imperfect) measure estimated using data from the US Annual Survey of Manufacturing and the US Economic Census. We also show that our estimates are robust to dropping one state and one industry at a time, ensuring that our result is not being driven by any one state or industry.

Our paper is related to multiple strands of literature. First, it is related to the literature exploring the impact of land market institutions on several outcomes. This includes impacts of land rental activity in Indian agriculture (Bolhuis, Rachapalli and Restuccia, 2021; Deininger, Jin and Nagarajan, 2008), impact of land consolidation program in the Indian state of Karnataka on industrial activity (Blakeslee et al., 2021) and impact of land input misallocation on output misallocation in Indian manufacturing plants (Duranton et al., 2015). Our paper is closely related to Sood (2022) and Pal, Roy Chowdhury and Saher (2022) who use the angle of land fragmentation to check for impact on firm outcomes. Our paper differs from them on three aspects. First, we incorporate a stricter empirical test which looks for systematic differential impact of frictions along the dimension of land requirement of industries. This allows us in credibly ruling out any alternative explanations based on unobservable variations at state-year and industry-year levels and hence, make our evidence causally more convincing. Second, we show that the salience of land fragmentation on plant outcomes is actually due the land market frictions like poor land records and low rental activity. Finally, the design of our empirical test allows us to extend our analysis to the services sector and provide evidence on why there may be no effect. Our paper is also related to the recent literature which explores the impact of land market institutions in other countries: Tanzania (Manysheva, 2022), China (Adamopoulos et al., 2022), Malawi (Chen, 2017) and the US (Herkenhoff, Ohanian and Prescott, 2017).

Second, it is related to the literature exploring factors affecting manufacturing growth in India. This includes impact of contract enforcement on organisation of production (Boehm and Oberfield, 2020), effect of electricity shortages on industrial growth (Allcott, Collard-Wexler and O'Connell, 2016), impact of small scale industry promotion on growth of plants (Martin, Nataraj and Harrison, 2017), impact of capital market integration on capital misallocation (Bau and Matray, 2020), impact of capital and labor misallocation on aggregate TFP (Hsieh and Klenow, 2009) among others.

Finally, given that we show the differential impact of land market frictions on manufacturing and services sector, our paper is related to the literature exploring structural transformation experience of India, which is highlighted by exceptional services growth. This includes unequal effects of services-led growth (Fan, Peters and Zilibotti, 2021), role of services TFP growth in driving India's structural transformation (Verma, 2012), role of skill heterogeneity across manufacturing and services sector in driving India's sectoral trends (Serrano-Quintero, 2021), role of modern services in driving services sector growth (Eichengreen and Gupta, 2011), among others.

The rest of the paper is organised as follows. Section 2 describes the datasets used for our analysis. Discussion on identification strategy and construction of key variables is in section 3. Section 4 discusses the results on manufacturing sector in detail, including heterogeneity in sub-section 4.1, mechanisms in sub-section 4.3, and robustness in sub-section 4.4. Section 5 discusses the cross-section results of services sector and its contrast with manufacturing sector result. Finally, section 6 concludes.

2 Data

We use data from three key surveys for our analysis: Input Survey conducted by Ministry of Agriculture & Farmers' Welfare, Annual Survey of Industries (ASI) and Service Sector in India Survey.

2.1 Input Survey (Agriculture)

The state level data on fragmentation of land is sourced from Input Survey conducted by Ministry of Agriculture & Farmers' Welfare.[5] Input Surveys are conducted every five years and the survey years relevant for our analysis are: 2001-02, 2006-07, 2011-12 and 2016-17.

The advantage of using Input Survey over Agriculture census is that it also reports data on "parcel fragmentation" along with data on "operational holding fragmentation", unlike Agriculture census which reports only the data on "operational holding fragmentation".[6] Given that we intend to capture the difficulty in acquisition of land through land fragmentation, the relevant unit of fragmentation for us is the parcel fragmentation. This stems mainly from the fact that whenever a plant tries to expand by purchasing land, it will try to do so by acquiring the adjoining *parcel* of land, and not the holding of land

[5]These surveys are conducted in the year succeeding the survey year of Agriculture Census and their objective is to collect information on various agriculture inputs like chemical fertilizers, pesticides, machinery, etc. along with fragmentation of land. The input survey randomly covers 40 % of the villages which were selected in the phase-II of Agriculture Census conducted in the preceding year.

[6]Operation holding is defined as *"All land which is used wholly or partly for agricultural production and is operated as one technical unit by one person alone or with others, without regard to the title, legal form, size or location"*, while parcel is defined as *"All land entirely surrounded by land of other holdings or by land not forming part of any holding. It may consist of one or more cadastral units, plots or fields."* (Govt of India, 2021)

which is most possibly spread across different locations. We use average parcel size (in hectares) in a state to measure land fragmentation. A state with lower average parcel size will indicate higher land fragmentation in that state and vice versa.

2.2 Annual Survey of Industries

The micro-data on the outcomes of manufacturing plants is sourced from Annual Survey of Industries (ASI), which is conducted every financial year. The scope of coverage of ASI extends to all registered manufacturing plants in the country, registered under Factories Act, 1948. The unit of enumeration in ASI is a plant, which is referred as "factory" in the survey.[7]

There are two benefits of using ASI for studying the manufacturing sector. First, ASI provides us with plant identifier called "Factory Code", which allows us to link plants across survey years, and hence, enabling construction of a panel data set. Second, as has been noted by Sood (2022) and Duranton et al. (2015), ASI is one of the few datasets available which reports the value of land owned by a plant, separately from the value of building owned. This feature is not available even in manufacturing surveys of developed economies.[8] The value of land owned by plants allow us to estimate the technological requirement of land in an industry, which is a crucial element of our estimation strategy.

We use total output and total employment of a plant as an outcome measure for the plant. In order to match the availability of data on fragmentation from Input Survey, the relevant survey years from ASI for our analysis are: 2001-02, 2006-07, 2011-12 and 2016-17. On the other hand, to estimate the technological requirement of land in an industry, we use balance sheet data on land owned by plants from all the ASI survey years, starting from 2001-02 to 2016-17.

ASI reports industry code of plants at 5-digit level NIC code (National Industrial Classification). The NIC code changed twice during our analysis period: ASI 2001-02 provides

[7]For the purpose of sampling, ASI divides the plant into two categories: Census scheme and Sampling scheme. Census scheme contains large plants, typically with more than 100 employees, all of which are surveyed every year. On the other hand, the registered plants which do not fall in the Census scheme, are covered under Sampling scheme, which are covered once every three or five years. Since sampling frequency varies across the two schemes, we use sampling weights provided by ASI to estimate regressions.

[8]For instance, the Annual Survey of Manufactures conducted by the US Census Bureau does not report the asset value of land separately

NIC 98 codes, ASI 2005-06 provides NIC 04 codes, while ASI 2011-12 and 2016-17 provides NIC 08 codes. Given that the concordance for different versions provided by NIC is not one-to-one at 3 digit or granular level, we use industry classification at 2-digit NIC level for our analysis, which provides us with 20 broad industry categories for the manufacturing sector. Table 1 lists the industry categories.

2.3 Service Sector in India Survey (NSSO)

The micro-data on the outcomes of service sector firms is sourced from Service Sector in India Survey conducted by NSSO as a part of its 63rd round. Unlike the ASI, the Service Sector Survey was conducted only once during 2006-07, which also limits our analysis to the cross-section of these firms. Like ASI, we focus on 2 digit level NIC classification, which provides us with 15 broad categories of services like hotels, restaurants, transport, storage, communication, financial intermediation, etc.[9]

Unlike ASI data, Service Sector Survey does not report the value of land owned by plants separately. Instead, it reports value of "land and building" in the balance sheet of plants. We use this variable to estimate the technological requirement of land in an industry.[10]

Other data sources: For robustness and mechanism, we use data from a few other sources. We calculate land requirement of industries for the plants in the US as an alternative measure for land requirement. For this, we obtain data from Annual Survey of Manufacturing (ASM) which provides industry level estimates of capital expenditure of building and other equipments. The data on number of firms within each industry in the US is sourced from the US Economic Census. Next, we obtain data on net state domestic product, state level literacy rates and share of agriculture in state domestic product from the Handbook of Indian States maintained by the Reserve Bank of India. In order to estimate the extent of land disputes in a state, we source age of pending cases related to land disputes from National Judicial Data Grid (NJDG) (Verma, 2018). Finally, in order to deflate the output of plants measured in different years in ASI, we use Wholesale Price

[9] Table 2 provides the list of industry categories from Services Sector Survey

[10] The firms reported in Service Sector Survey are classified into two categories: Own Account Enterprise (OAE) and establishments. OAE are defined as *"An enterprise, which is run without any hired worker employed on a fairly regular basis"*, while an establishment is defined as *"An enterprise which employs at least one hired worker on a fairly regular basis."* (Govt of India, 2009). Given that OAE will not provide any variation in total employment in firm level regressions, we drop OAE from our analysis sample.

Index (WPI) at 2-digit NIC code level, which is available yearly from the website of Office of Economic Advisor, Ministry of Commerce & Industry.

We apply standard data cleaning procedures on the firm level micro-data, which has been widely used in the literature. First, to limit the influence of outliers in our analysis, we *winsorize* the output, employment and land value variables at the industry-year level.[11] Second, we drop the plants not belonging to manufacturing sector in ASI and those not belonging to services sector from Service Sector in India Survey. Third, we focus only on plants whose status is reported as "active" in the ASI survey and the ones who haven't switched industries during our analysis period. Fourth, we drop firms located in North Eastern States, Union Territories, Jammu & Kashmir and Goa. And finally, given that we exploit the panel nature of ASI dataset for our analysis, we restrict the sample in ASI to the firms who appear at least twice during our analysis period.

Table 3 provides the summary statistics. The table highlights the clear contrast in the scale of operation of manufacturing plants and services sector firms. The output and employment of manufacturing plants in our sample is much higher compared to services sector firms.

3 Empirical Strategy

The objective of our empirical strategy is to capture how variation in the difficulty of acquiring land across states affect firm outcomes. One strategy to estimate this can be the simple comparison of state-level land market frictions and firm outcomes over time. However, the problem with this strategy is that unobservables at the level of state and over time, correlated with land fragmentation and firm outcomes, can confound our estimates. There can be many explanations which can influence the result. For instance, states with highly fragmented land can have lower productivity in agriculture, which restricts the movement of labor out of agriculture, which further hampers outcomes for manufacturing plants because of reduced labor supply (Huneeus and Rogerson, 2020).

In order to rule out such alternative explanations, we follow a stricter empirical strategy: compare the outcomes of firms in industries whose technological requirement of

[11]For every 2-digit industry every year, we focus on the distribution of these variables and replace the values greater than 99^{th} percentile with that of 99^{th} percentile and those lesser than 1^{st} percentile with that of 1^{st} percentile.

land is higher to those in industries whose technological requirement of land is lower, in states with high land market frictions relative to states with low land market frictions. If it turns out that relative performance of firms in high land requiring industries worsen with increase in land market frictions, we can credibly conclude that land market frictions negatively impact the outcomes of firms. Note that this stricter test has the capacity to rule out many alternative explanations and therefore, helps in consistent estimation of the impact of land market frictions. Continuing with the above example, while reduced labor supply can impact the growth of manufacturing plants due to low agricultural productivity in states with highly fragmented land, it is not clear why it should impact the growth of plants in higher land requiring industries *systematically* more.

The key idea behind our empirical strategy is that plants in industries which require more land, will have to acquire a larger area of land in order to expand, relative to those in industries which require less land. Since presence of land market frictions imposes a cost on acquiring parcels of land, the total costs faced by the large land using industries will be higher compared to low land using industries. An additional advantage of our stricter test, from the econometric viewpoint, is that the estimate will be exploiting a richer variation in the main independent variable, which varies not only at the level of state, but also at the level of industries. In order to execute this strategy, we exploit the variation of two key variables: land fragmentation and technological requirement of land by industries.

3.1 Variation in Land Fragmentation

We use data on fragmentation of land to proxy for the difficulty in acquisition of land in a state. This stems from the fact that if acquisition of land involves an additional cost due to land market frictions (like restrictive land use policies, poor land records, etc.), then the acquisition cost of the same area of land in two states with different land fragmentation can be different. One will have to acquire more parcels of land in a state with more land fragmentation, hence, more transaction costs compared to a state with less land fragmentation.[12] We use average parcel size (area per parcel) in a state as a proxy for land fragmentation in that state. States with low average parcel size will depict higher land fragmentation and hence more frictions for firms to expand.

[12]This metric of using land fragmentation for measuring difficulty in acquiring land by firms has been used in some form or the other in the recent literature (Sood, 2022; Pal, Roy Chowdhury and Saher, 2022).

For the cross-section specification, our strategy uses the variation in land fragmentation across states. This cross-sectional variation in land fragmentation can mainly arise due to the state level variation in the level of land ceilings imposed during the wave of land ceiling legislation implemented across states during 1970s (Pal, Roy Chowdhury and Saher, 2022). It can also reflect the legacy of different colonial land tenure systems across states in India (Banerjee and Iyer, 2005).

For the panel specification, our strategy uses the variation in *change over time* in land fragmentation across states. This can occur due the practise of land inheritance where the inherited land can get split across multiple children. This process can become salient due to population pressure and due to economic forces restricting movement out of agriculture (Jha, Nagarajan and Prasanna, 2005; Niroula and Thapa, 2005).

3.2 Variation in Land Requirement of Industries

We intend to use the value of land owned by firms in an industry to get a proxy for the technological requirement of land by industries. However, one problem in calculating this value for an average firm in the industry is that the amount of land owned by an average firm might itself be affected by land market frictions faced by them. In order to tackle this problem, we use the average value of land owned by firms between 90^{th} to 95^{th} percentile of employment distribution within an industry. Our assumption is that these "top" firms within an industry would have faced relatively lesser land market frictions compared to an average firm, and hence variation in the amount of land owned by these firms across industries can better reflect the variation in technological requirement of land across industries.

In order to construct this estimate, we first select the firms between 90^{th} to 95^{th} percentile of employment distribution for every industry-year pair for all survey years of ASI from 2001-02 to 2016-17. Next, given that what we observe is the value of land owned, which is prone to change over years due to changes in land prices, we use the residuals calculated after regressing the value of land owned by firms on year fixed effects. The industry-wise mean values of these land value residual is used as technological requirement of land of the industries. For the services sector, we repeat the same exercise with 2006-07 Service Sector Survey, but skipping the step of estimating residuals, since we only have one year.

Table 1 provides the ranking of manufacturing industries based on the land values constructed as per the above mentioned procedure. Industries related to manufacturing of transport equipments, petroleum products and basic metals constitute the top 4 industries using more land, while industries related to manufacturing of rubber, plastics, wearing apparel, furniture and wood products constitute the bottom 4 industries using less land. Table 2 provides a similar ranking for services sector industries.

We prefer using this measure compared to a scale-invariant measure of land intensity like percentage of land rental payments out of total payments. The main reason is that land fragmentation will pose frictions in expansion of plants only when the quantity of land to be purchased is higher. For purchase of small areas of land (for instance, less than the minimum average parcel size across states), the variation in difficulty of acquiring land will be very little across the land fragmentation of different states. Therefore, land fragmentation becomes salient only in transactions involving larger areas of land. This notion is different from the one where frictions affect *every* transaction of land, irrespective of its volume, which is relevant for the land intensity measures.

3.3 Regression Specification

The panel specification for our empirical strategy is given by

$$\mathrm{Y}_{ijst} = \delta \cdot \text{Avg Parcel}_{st} \times \text{Land Value}_j + \beta \cdot x_{ijst} + \lambda_i + \alpha_{st} + \gamma_{jt} + \epsilon_{ijst}, \tag{1}$$

where Y_{ijst} denotes the outcome of manufacturing plant i, in industry j, located in state s, in year t. The key outcome variables for our analysis are output and employment of plants. λ_i denotes plant fixed effects, which controls for plant specific, time invariant unobservables like ownership, productivity, location, etc. More importantly, it helps in alleviating many of the concerns surrounding endogenous location of plants across states. Usage of plant fixed effects allow us to estimate the impact of fragmentation, by focusing on the change in land fragmentation that occurs *after* the plant has settled in that state. More on endogenous location is discussed in section 4.2 below. α_{st} denotes state-year fixed effects. These guard us against any state-year level variation that may be correlated with both parcel fragmentation and outcome of plants, but not systematically correlated along land requirement of industries. They help us in ruling out the alternative explanations (like agriculture productivity in the state) discussed above. Finally, γ_{jt} denotes industry-year fixed effects which control for any unobservable variation across industry as well as over time like industry level tariff rates, industry specific productivity growth, etc. Additionally, we include age of plant (x_{ijst}) as a plant-level time-varying control.

Our main independent variable is Avg Parcel$_{st}$ $\times$ Land Value$_j$ which is the interaction of average parcel size of the states and the land values (residuals) of the industries. Consequently, δ is our coefficient of interest. Because of the two dimensional fixed effects, equation (1) becomes a saturated specification where the variation used to identify δ is the simultaneous variation of change in parcel size over time across states *and* the variation in land values across 20 manufacturing industries. Accordingly, the only residual variation which can confound the estimates of δ are the ones varying simultaneously at the level of state, industry *and* time. Therefore, our estimate of δ is immune to any alternate explanation based any state-year, industry-year or state-industry level variation. Section 4.2 below discusses this in greater detail.

Note that since equation (1) is a panel specification, it will only be used for constructing estimates for the manufacturing sector. For services sector, due to paucity of detailed micro-data with repeated cross section or panel characteristics, we rely on a cross-section version of equation (1). The regression specification is given by

$$\mathrm{Y}_{ijs} = \delta \cdot \text{Avg Parcel}_s \times \text{Land Value}_j + \beta \cdot x_{ijs} + \alpha_s + \gamma_j + \epsilon_{ijs}, \tag{2}$$

where Y_{ijs} denotes outcome of firm i, belonging to industry j and located in state s. α_s denotes state fixed effects and γ_j denotes industry fixed effects. We include a dummy variable indicating if the firm is located in urban area as the firm level control variable (x_{ijs}). The variation being used to estimate δ is the simultaneous variation of average parcel size across states and that of land requirement across industries. Given the fixed effects, the only residual variation which can confound the estimates of δ are the ones varying simultaneously at the level of state *and* industry.

If land market frictions inhibit firm growth, we expect the industries with higher land values to perform relatively better when average parcel size increases (less land parcel fragmentation). Therefore, the test to check the impact of land market frictions is to test whether δ is positive and significant.

Finally, we cluster the standard errors at the level of state, which provides us with 20 clusters. Since asymptotic properties of cluster robust variance-covariance matrix may not hold with low number of clusters, we also provide the p-values reported from the procedure of Wild Cluster Bootstrap (Roodman et al., 2019).

4 Manufacturing Sector

4.1 Main Results

Table 4 presents the estimates of our empirical test using log of output of plants as the outcome variable. Column 1 runs the regression equation (1) with plant fixed effects and state-year fixed effects. Column 2 presents our preferred specification with plant fixed effects, state-year fixed effects as well as industry-year fixed effects. The coefficient of δ in both specifications is positive and significant, indicating that land market frictions (through the channel of land fragmentation) have significant and negative impact on the growth of output of plants.

The other main outcome variable that we consider is the employment of plants. Table 5 report the estimates of equation (1) by taking employment of plants as the outcome variable. Columns 1 and 3 run regression equation (1) with plant fixed effects and state-year fixed effects. Columns 2 and 4 present our preferred specification with plant fixed effects, state-year fixed effects as well as industry-year fixed effects. While the estimate of δ for the full sample of 20 industries is insignificant for both the specifications in columns 1 and 3, it becomes positive and significant when we restrict our sample to the top 10 industries ranked according to their land values (column 2 and 4).[13] This indicates that land market frictions also negatively impact the growth number of employees in a plant.

The estimates from our preferred specification suggest that the 5-year growth of output of plants in industries with high land requirement (75^{th} percentile) *slows down* by 11.8 percentage points compared to those in low land requiring industries (25^{th} percentile), as state average land parcel size reduces from 75^{th} to 25^{th} percentile. This number is 9.9 percentage points for employment. Given that the average 5-year growth of output and employment is 34.5% and 9.6%, respectively, the effects that we find are sizeable.

In the next few tables, we investigate the heterogeneous impacts of land market frictions. Table 6 demonstrates the impact of land market frictions separately for old and

[13]While the sample of top 10 is "half" based on the number of industries, the number of plant-year observations is still around 70% of the full sample.

young plants. A firm is classified as young if its age is lower than the median age in the corresponding industry-year group. We expect the land market frictions to affect younger plants more compared to older plants. Older plants have higher chances of forming ties with the local neighbourhood as well as local bureaucrats which can make land transactions relatively frictionless for them. Estimates of Table 6 show that it is indeed the case. The impact on output and employment for younger plants (columns 3 and 4) is around twice compared to older plants (columns 1 and 2).

Next, we study heterogeneity along the dimension of land requirement of industries. Given that industries requiring more land are the ones who are expected to be constrained more due to land market frictions, we expect δ to be higher for them. Estimates reported in Table 7 confirm this. We present the estimates from our preferred specification for the samples restricted to top 10 and bottom 10 land using industries, respectively. The impact on output for plants in top 10 land using industries (column 1) is 1.6 times higher compared to those in bottom 10 industries (column 3).

The third heterogeneity we study is along the dimension of ownership of plants. We expect the effect of land market frictions to primarily arrive from the sample of plants owned by a private entity compared to the ones owned by a public entity. Publicly owned plants are expected to face lower frictions given their possible connection to the bureaucrats and their ability to use eminent domain for acquiring land. Table 8 reports the estimate of δ from our preferred specification for the samples restricted to privately owned plants (columns 1 and 2) and publicly owned plants (columns 3 and 4), respectively. Consistent with our expectation, we find that the estimate of δ is positive and significant for the privately owned plants, while it is insignificant for the sample of publicly owned plants.[14] Heterogeneity of δ along all these relevant dimensions further strengthens the causal appeal of our main results.

Finally, we also look at two other outcome variables. First, we look at the effect of land market frictions on the extensive margin – entry of plants. We calculate the number of plants that start their initial production during our analysis period at the industry-

[14] One drawback of this regression is that the publicly owned plants constitute a very small part of our analysis sample.

state-year level. Using this, we estimate the following specification

$$\text{Plant Entry}_{jst} = \delta \cdot \text{Avg Parcel}_{st} \times \text{Land Value}_j + \theta_{js} + \alpha_{st} + \gamma_{jt} + \epsilon_{ijst}, \tag{3}$$

where θ_{js} denotes industry-state fixed effects. Column 1 of Table 9 shows that entry of plants is also affected in the same way as output and employment, indicating that land market frictions also impact plants on the extensive margin. The estimates suggest that number of plants that enter in industries with high land requirement (75^{th} percentile) should be *lower* by 6 plants compared to those in low land requiring industries (25^{th} percentile), as state average land parcel size reduces from 75^{th} to 25^{th} percentile. Compared to this, the average number of plant entry at industry-state-year level is 43.

Second, we look at the effect on the labor productivity of plants. We estimate labor productivity by taking the ratio of output to employment for every plant and use this as an outcome variable in our preferred specification of equation (1). Column 2 of Table 9 shows that labor productivity is impacted in the same way as output and employment. The estimates suggest that the 5-year growth of labor productivity of plants in industries with high land requirement (75^{th} percentile) *slows down* by 5.8 percentage points compared to those in low land requiring industries (25^{th} percentile), as state average land parcel size reduces from 75^{th} to 25^{th} percentile. In comparison to this, the average 5-year growth of labor productivity in our analysis sample is 24.3%.

4.2 Ruling out alternative explanations

The state-year fixed effects and industry-year fixed effects in equation (1) rule out many alternative explanations based on state-year or industry-year level unobservable variation, which are not necessarily uncorrelated with our main independent variable $\text{Avg Parcel}_{st} \times \text{Land Value}_j$. The only remaining threat to our identification are the unobservables varying *simultaneously* at the level of state, industry and time. In this section, we argue that such specific unobservable variation do not pose any significant identification challenge for the consistent estimation of δ.

The first set of unobservable variation can be regarding alternate explanations of omitted variable bias or reverse causality related to labor or capital intensity of industries and parcel fragmentation. For instance, it may be the case that growth of labor intensive industries pull labor out of agriculture and therefore make the process of parcel fragmentation slower through inheritance channel. To rule out such explanations, we show that our main effect along the land requirement of industries is different compared to that along labor intensity or capital intensity of industries. In order to test the same, we include Avg $\text{Parcel}_{st} \times$ Lab. Intensity_j and Avg $\text{Parcel}_{st} \times$ Cap. Intensity_j as additional controls in equation (1).[15] If the concerns mentioned above are indeed true, we should notice a sharp drop in estimate of δ. Columns 2 and 3 of Table 10 show that the estimate of δ is unaffected for output by inclusion of the two controls. For employment, columns 2 and 3 of Table 11 show that the estimate of δ *increases* after controlling for the above two variables. This shows that our main result is robust to any alternative explanations which relate to capital or labor intensity of industries.

The second set of unobservable variation can be regarding alternate explanations related to causes and consequences of state land fragmentation over time. As noted in section 3.1, land fragmentation can change over time because of population pressure and economic forces restricting the movement out of agriculture. To rule out any alternative explanations based on these factors, we include Per Capita $\text{Income}_{st} \times$ Land Value_j, $\text{Literacy}_{st} \times$ Land Value_j and Agri. $\text{Share}_{st} \times$ Land Value_j as additional controls in equation (1). Columns 4, 5 and 6 of Table 10 show that the estimate of δ is relatively unaffected for output by inclusion of the three controls. The maximum drop in the estimate δ is by only 13% when we include the first of the above three controls. For employment, columns 4, 5 and 6 of Table 11 show that estimate δ is robust to the inclusion of these three controls and, if anything the magnitude increases. This confirms that the effect we find along the margin of land requirement of industries occurs only in response to change in parcel fragmentation over time and not due to change in economic factors related to it – per capita income, literacy rate and share of agriculture in state domestic product.

The last concern regarding the main results will be the endogenous location of plants across states according to the land fragmentation of states. It might be the case that most of the plants in industries using more land are located in states with less fragmentation, or better plants in general may have located in states with lesser fragmentation. We tackle much of this problem by inclusion of plant fixed effects. They control for time invariant

[15] Labor intensity of an industry is calculated by taking the average of the ratio of total wage payment to total output of the plants in the industry. Capital intensity is calculated by taking the average of the ratio of value of total assets to total output of the plants in the industry.

plant level unobservables, which essentially helps in estimating the effect of fragmentation of land on plant outcomes *after* the plant has settled in a particular state.

To investigate this further, we plot the distribution of plants across the states within every industry in Figure 1. The x-axis measures the average parcel size of each state over the 4 years. Plot 1 shows distribution of plants across states in the least land using industry while plot 20 shows distribution of plants in the most land using industry. If the plants in industries using more land were systematically located in states with higher parcel size, we should have noticed the gradual shift in distribution of plants towards right as we move from plot 1 to plot 20. Such shift is not visible in the figure except the outlier state of Punjab (with average parcel size around 3 hectares). As a quantitative test, we estimate the simple bivariate regression

$$\ln(\text{Land Value}_j) = \alpha + \beta \cdot \text{Avg Parcel}_s + \epsilon_{ijs}, \tag{4}$$

which regresses the log of land value of the industry to which the plant belongs to against the average parcel size of the state in which plant is located. If endogenous location of plants occurred systematically, then we should get positive and significant estimate of β. Table 12 shows that the estimate is insignificant for the full sample (column 1) according to the p-values reported by the Wild Cluster Bootstrap procedure. The estimate further drops and becomes insignificant once we drop the plants located in outlier state – Punjab (column 2). This result further eliminates any concern related to the endogenous location of plants.

We reconcile the above result along with the result on extensive margin by noting that the rate of entry of new plants during our period is low. The relatively small effect size in addition to this makes the effect along extensive margins to be small enough to affect the entire cross sectional distribution of plants across states.

4.3 Mechanism

In this section, we attempt to show that the effect of land fragmentation on plant outcomes is actually due to the land market frictions like poorly documented land records, restrictive land use policies, etc. Our first test to capture this is to check whether the impact of land fragmentation (δ) is higher for states with problems of poor land records. In order to proxy for the extent of poor land records issue in a state, we use the age of pending cases related to land disputes in a state.[16] Table 13 presents the estimates of δ from our preferred specification after dividing the sample into two parts: states with age of pending cases related to land dispute above the median age (columns 1 and 2) and the ones with pending age below the median age (column 3 and 4). The impact on output and employment for plants located in states with more land disputes (columns 1 and 2) is around 3 times and 4.6 times higher, respectively, compared to those located in states with less land disputes (columns 3 and 4).

On similar lines, we test whether the impact of land fragmentation (δ) is higher for states with lower land rental market activity. The rental market activity of a state can reflect the overall ease with which land transaction can take place in that state. A state with lower land rental market activity can reflect difficulty in land related transactions and hence, more land market frictions. We borrow the estimates of state land rental market activity from Bolhuis, Rachapalli and Restuccia (2021) who calculate the proportion of agricultural households renting in or out a positive amount of land in a state from Indian Human Development Survey (IHDS) dataset. Using these estimates, we classify top 10 land renting states as states with high land rental market activity and the bottom 10 states as those with low land rental market activity. Table 14 demonstrates that the impact on output and employment for plants located in states with low land rental market activity (columns 1 and 2) is around 1.73 times and 6.6 times higher, respectively, compared to those located in states with high land rental market activity (columns 3 and 4).[17] The two tests above provide convincing evidence that the effects of land fragmentation on plant outcomes is being driven by land market frictions.

Finally, we attempt to show that the effect of land fragmentation on plant outcomes actually takes place through the channel of difficulty in acquiring land. To test this, we check whether the value of land owned by plants in industries requiring more land grows relatively slow compared to those in industries requiring less land, as land in a state gets more fragmented. To execute this test, we estimate our preferred specification (equation (1)) by taking the log of land value of firm i in year t as the outcome variable.

Table 15 reports the estimates of this exercise. While the coefficient of interest is positive and insignificant for the full sample, it increases and becomes significant for the

[16] This data has been extracted from National Judicial Datagrid (link)

[17] Note that the coefficient of output in column 1 is a little bit imprecise.

sample of top 10 land requiring industries (though the estimate is a little imprecise based on Wild Cluster Bootstrap p-value). The magnitude of δ is comparable to that of output for the top 10 land requiring industries. We treat this result as a suggestive evidence that the impact of land fragmentation on plant outcomes would have been driven through the channel of difficulty in acquiring land.

4.4 Robustness

4.4.1 Alternative Measures for Land Requirement

In this section, we show that our main results is robust to using different ways to capture land requirement of industries. First, instead of using the land values (residuals) variable in the interaction term of equation (1), we use a dummy variable which takes value 1 if the land value (residual) of the industry is greater than the average land value (residual) and 0 otherwise. Columns 1 and 2 of Table 16 show that the main result is robust to this measurement. For employment, the estimate of δ is positive and significant, even for the full sample of 20 industries.

As a second measure, we use ranks of the industries based on land requirement given by the land values (residuals). The industry requiring the least land is assigned rank 1 while the one requiring the most land is assigned rank 20. Columns 3 and 4 of Table 16 show that the main result is robust to this measurement. The estimate of δ is positive and significant. Both these results show that the ordinal ranking provided by the land values (residuals) holds meaningful information to derive our main results.[18]

Next, and most importantly, we attempt to estimate the land values of industries using the data from the US Annual Survey of Manufacturers (ASM) and the US Economic Census. The US ASM provides industry-wise measure of capital expenditure on buildings and other structures. While this is an imperfect measure of land requirement of the industries compared to what is available in ASI, the appeal of using this measure is its exogeneity to the land market conditions in India. We sum up this measure for each industry from 2002 to 2016 and divide it by the average number of firms in respective industries during this period, which is sourced from the US Economic Census. Columns

[18] Additionally, the main result remains unaffected when we use the average of land values taken from all the survey years in 2002-2017 period instead of taking residuals from regressing land values on year dummies. The main results is also robust to not using survey weights while executing our regressions.

1 and 2 of Table 17 shows that the main results is robust to this foreign measure of land requirement, even for the full sample of 20 industries for employment. Columns 3 and 4 of Table 17 show that the results is also robust to using a dummy variable which takes value of 1 when land requirement based on the US measure is above average and 0 otherwise. This result rules out any concerns related to the endogeneity of land values measure used in our main results.

4.4.2 Other Robustness Checks

Next, we check whether our main result is being driven by any particular state or one particular industry. For this, we execute our main specification for both output and employment by dropping one state at a time and one industry at a time, respectively. Figures 2 and 3 show the stability of coefficient (δ) by dropping one state a time time for output and employment, respectively. Similarly Figures 4 and 5 show the stability of coefficient (δ) by dropping one industry at a time for output and employment, respectively. The remarkable stability of the magnitude of δ exhibited in all the 4 plots ensure that none of our main results is being driven by any one particular state or industry.[19]

Finally, since the land values (residuals) were constructed using plants between 90^{th} to 95^{th} percentile of employment distribution for every survey year from 2001-02 to 2016-17, we check whether results continue to hold if we drop these firms from our analysis sample. Table 18 shows that the main result is robust to excluding this particular subsample.

5 Services Sector

For services sector firms, due to paucity of detailed microdata with repeated cross section or panel characteristics, we rely on a cross-section specification given by equation (2). Table 19 first shows that the main result for manufacturing sector plants continue to hold for the top 10 land requiring industries in the cross-section specification.[20] These estimates are constructed using observations from ASI 2006-07, which formed part of our previous

[19] Note that for employment, the significant result was coming out of top 10 land requiring industries, hence, the robustness test in Figure 5 is carried out with those 10 industries. For the two industries where 95% confidence interval includes 0, the result is still significant at 10% level.

[20] Note that result for log of output is only a little bit imprecise.

analysis sample. Table 20 shows that similar results are not observed for firms in services sector. Even after focusing on the top 8 land using industries within services (columns 2 and 4), the coefficient still remains insignificant and, if anything, it is negative in sign.

We investigate if we can observe positive and significant effect for services by focusing on specific sub-samples and using alternate ways to measure land requirement. First, we focus on a sub-sample which includes big firms within each industry, with the expectation that land fragmentation should impact bigger firms more. We classify a firm as a big firm if its employment size is larger than the median employment in its industry. Table 21 shows that we still do not find positive and significant effects, even after focusing on the sample of top 8 land requiring industries (columns 2 and 4).

Next, we use a land dummy variable to indicate land requirement of industries. The dummy variable takes value 1 if the land requirement of the industry is greater than the average land requirement of the 15 industries and 0 otherwise. Table 22 shows that usage of this variable does not give us positive and significant results. As a further step, we use land rank of industries, constructed using land values, to measure industry-wise land requirements. The industry requiring the least amount of land is assigned rank 1, while the one requiring the highest amount of land is assigned rank 15. Table 23 shows that usage of land rank variable does not give us positive and significant results, even after focusing on the sample of top 8 land requiring industries (columns 2 and 4). This shows that even the ordinal information about the ranking of land requirement of services sector industries fail to show any effect of land market frictions on firm outcomes.

Finally, we drop the firms between 90^{th} to 95^{th} percentile of employment distribution in every industry - the ones who contributed in estimating land value of the industry. Exclusion of these firms also does not provide positive and significant results as shown in Table 24, even after focusing on the sample of top 8 land requiring industries (columns 2 and 4).

We interpret this null result for the service sector firms as a suggestive evidence that land market frictions impact outcomes of manufacturing plants disproportionately more compared to services sector firms. We rationalize this contrast in result by using two facts. First, as shown by the summary statistics in Table 3 as well as in Figure 6, the land requirement of industries in services sector is much lower compared to those in manufacturing sector. The average land requirement for the 20 manufacturing industries is more than 5 times that of the 15 services industries.[21] The distribution of land requirement of service sector industries in Figure 6 is sufficiently to the left of the distribution of land requirement of manufacturing sector industries. This can contribute to the null result since variation in fragmentation of land can become irrelevant for growth of a firm when the land requirement of that firm is small to start with.

Second, the employment size of services sector firms may not be as much tied to the land owned by it as compared to manufacturing sector. For manufacturing plants, land can be a crucial input given that without sufficient land, it might not to be possible to setup capital equipment like plant and machinery to carry out production. Therefore, even if land fragmentation may not allow services sector firms to expand their land, their employment size and other outcomes may be affected little given that land may not be as essential an input for services sector firms as it is for manufacturing plants. To check for this, we estimate the simple regression equation

$$\ln(\text{Emp}_{ijs}) = \beta \cdot \ln(\text{Land Value}_{ijs}) + \alpha_s + \gamma_j + \epsilon_{ijs}, \tag{5}$$

which regresses the employment size of a firm to the value of land owned, after incorporating state and industry fixed effects. Estimates in Table 25 shows that a 1% increase in the value of land owned by manufacturing plant is associated with 0.36% increase in employment size of that plant, while this increase is only 0.23% for services sector firms. This highlights that employment size and land owned are less tied up for services sector firms compared to manufacturing plants.

6 Conclusion

Our paper has two key contributions to the literature. Our first contribution lies in designing and implementing a convincing empirical strategy to test for the impact of land market frictions on the performance of firms. Our test concludes for negative impacts of land market frictions on performance of firms only when firms in industries that require relatively more land performs disproportionately worse when the state average land parcel size reduces.

[21] Given that land value for industries in services sector also includes the value of building, this contrast is further expected to be higher.

We implement this test for manufacturing firms and we conclude that land market frictions do have a negative and significant impact on the performance of manufacturing plants. Our strategy helps in ruling out any alternative explanations which are based on state level variation, which is correlated with land fragmentation and firm growth, but not correlated along land requirement of industries. This claim is bolstered by two results. First, we show that the differential effect of change in land fragmentation, that we find along the dimension of land requirement of industries, is independent of the differential effect along labor and capital intensity of the industries. Second, we show that differential effect along land requirement of industries occur only in response to changes in land fragmentation and not in response to changes in state level per capita income, literacy rate and share of agriculture in state domestic product. These results highlight the strictness of our empirical test. While state level per capita income, literacy rate and agriculture share in state domestic product maybe correlated with state level land fragmentation and can affect performance of firms, we do not expect them to have a systematic differential effect along land requirement of industries.

The heterogeneity in our main result further supports our hypothesis of land market frictions affecting firm performance. We find that the effect is higher for younger plants compared to older plants. The effect is higher for plants in industries requiring more land compared to those in less land requiring industries. Finally, the effect comes from the sample of privately owned plants, compared to publicly owned plants. All the above three results are along expected lines of a narrative on negative impacts of land market frictions. Moreover, we show that the effect of fragmentation is higher in states with more land disputes and in states with lower land rental activity. These two results provide evidence that the salience of fragmentation on plant performance is actually due to land market frictions like poor land records.

Our second contribution lies in finding the contrast in the effect of land market frictions on firm performance for the manufacturing and services sector. Using the cross-section specification, we show that while land market frictions have negative and significant impact on manufacturing plants, we fail to find any significant impact for services sector firms, irrespective of the way in which we try to measure land requirement of industries. We rationalise this contrast in results using two observations. First, the land requirement of services sector industries is very low compared to that of manufacturing industries – the average of industry wise land requirement for manufacturing sector is more than 5 times that of services industries. Second, we show that the employment size of services sector firms may not be as much tied to the land owned as compared to manufacturing plants. A 1% increase in value of land owned by a manufacturing plant is associated with 0.36% increase in its employment size, while this increase is only 0.23% for services firms.

These results together show that when the economic growth after the 1991 economic reforms and liberalisation in India created a pressure for reallocation of activities across sectors, land market frictions would have become a binding constraint for the growth of manufacturing plants disproportionately more compared to services firms. The focus of our paper has been on manufacturing and services sector. However, we conjecture that the same land frictions would have had impacts on the agriculture sector as well. Difficulty in selling the cultivable land might have negatively impacted the movement of labor out of agriculture. We leave the exploration of this question for future research.

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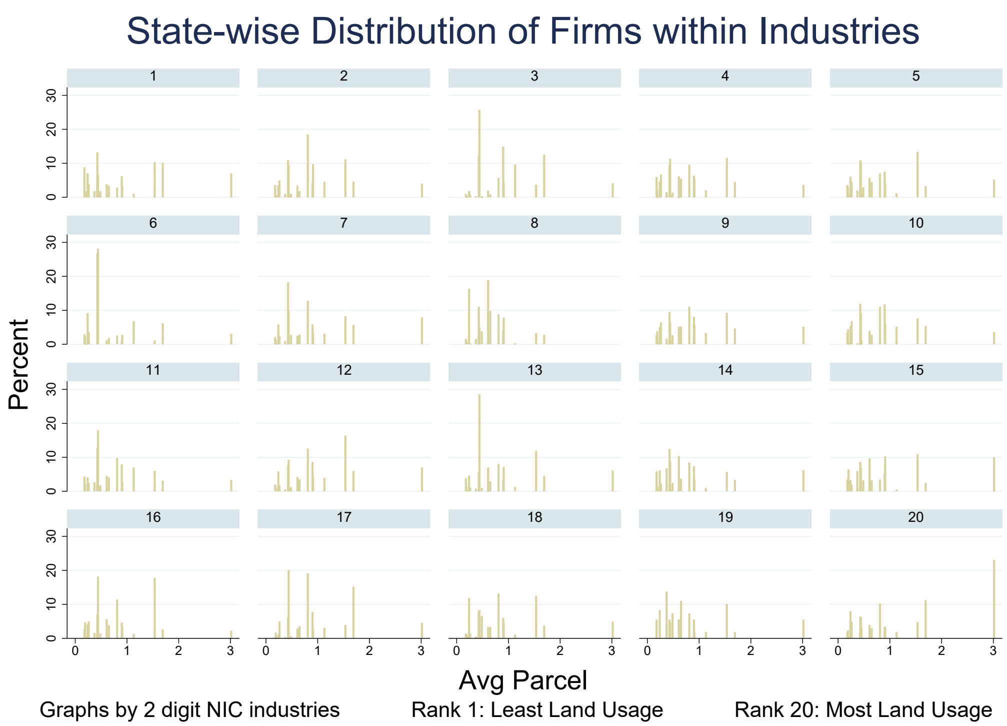
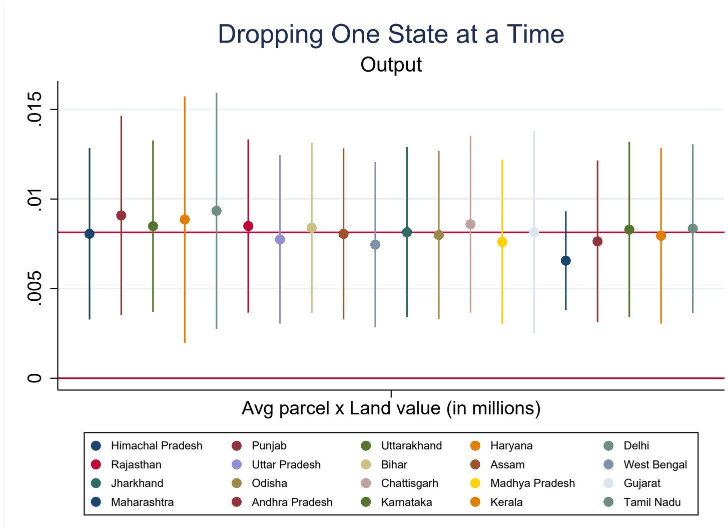
A Figures

Figure 1: Distribution of plants across states by Land usage of industries



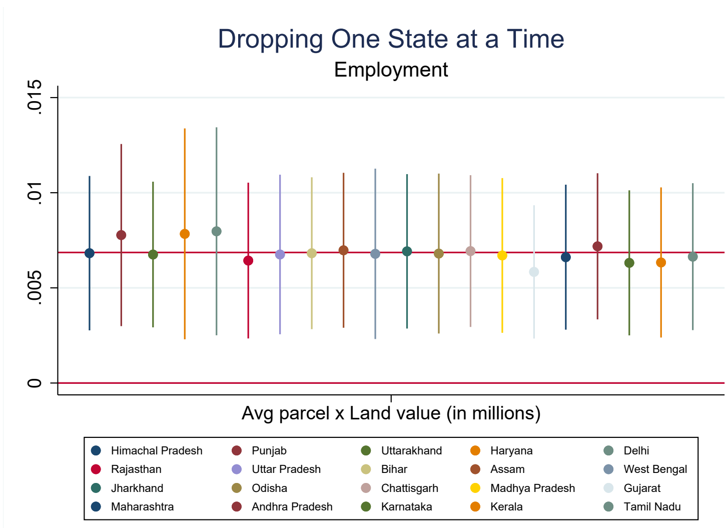
Notes: Each plot in the figure shows the distribution of plants in a particular 2 digit NIC manufacturing industry. x-axis shows the average parcel size of the state. The length of each bar within every plot shows the percentage of firms in a industry belonging to a particular state. Plot number 1 shows the distribution of firms in industry with lowest land value and plot 20 shows the same for industry with highest land value.

Figure 2: Robustness: Dropping One State at a Time (Output)



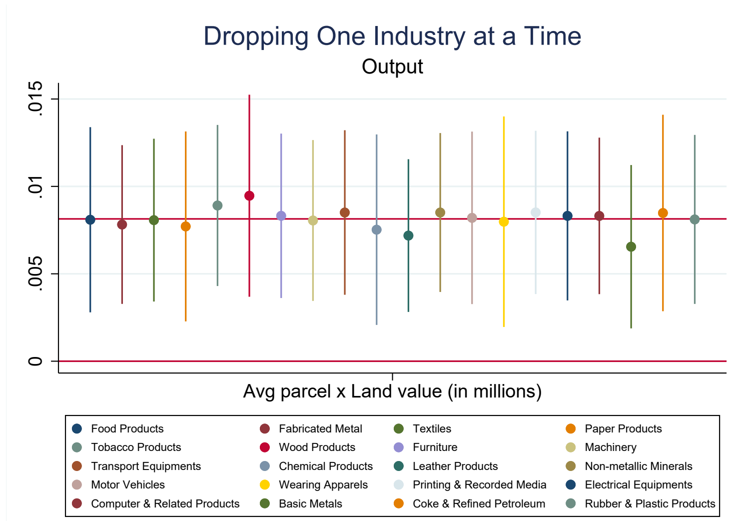
Notes: Each point in the figure reports the estimate of δ after dropping plant-year observations belonging to the corresponding state. 95% confidence intervals are reported. The red horizontal line shows the estimate of δ for the full sample. The sample of plants belong to the manufacturing sector.

Figure 3: Robustness: Dropping One State at a Time (Employment)



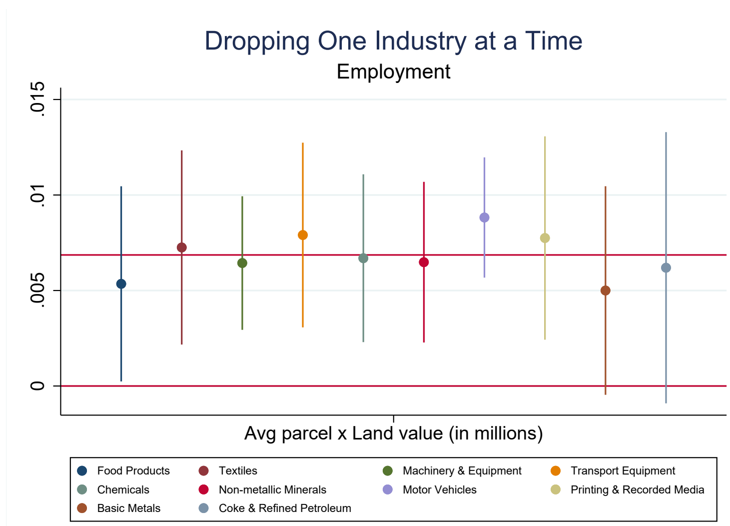
Notes: Each point in the figure reports the estimate of δ after dropping plant-year observations belonging to the corresponding state. 95% confidence intervals are reported. The red horizontal line shows the estimate of δ for the full sample. The sample of plants belong to the manufacturing sector.

Figure 4: Robustness: Dropping One Industry at a Time (Output)



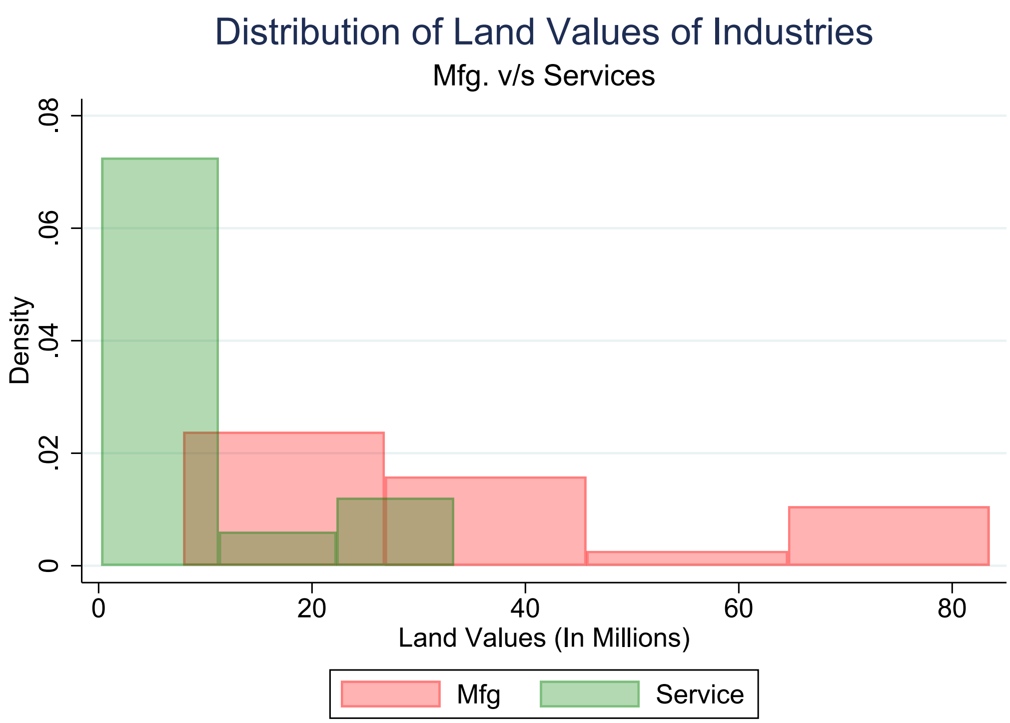
Notes: Each point in the figure reports the estimate of δ after dropping plant-year observations belonging to the corresponding industry. 95% confidence intervals are reported. The red horizontal line shows the estimate of δ for the full sample. The sample of plants belong to the manufacturing sector.

Figure 5: Robustness: Dropping One State at a Time (Employment)



Notes: Each point in the figure reports the estimate of δ after dropping plant-year observations belonging to the corresponding industry. 95% confidence intervals are reported. The red horizontal line shows the estimate of δ for the full sample. The sample of plants belong to the manufacturing sector.

Figure 6: Distribution of Industry-wise land requirement



Notes: The figure shows histogram of industry-wise land value for 20 manufacturing industries and 15 services industries. Industries are classified at 2-digit NIC level.

B Tables

Table 1: Ranking of Manufacturing Industries based on Technological Requirement of Land

Rank	Industry Description
1	Manufacture of other transport equipment
2	Manufacture of coke and refined petroleum products
3	Manufacture of basic metals
4	Manufacture of motor vehicles, trailers and semi-trailers
5	Manufacture of chemicals and chemical products
6	Manufacture of other non-metallic mineral products
7	Manufacture of food products
8	Manufacture of textiles
9	Manufacture of machinery and equipment n.e.c.
10	Printing and reproduction of recorded media
11	Manufacture of computer, electronic and optical products
12	Manufacture of electrical equipment
13	Manufacture of tobacco products
14	Manufacture of fabricated metal products, except machinery and equipment
15	Manufacture of leather and related products
16	Manufacture of paper and paper products
17	Manufacture of rubber and plastics products
18	Manufacture of wearing apparel
19	Manufacture of furniture
20	Manufacture of wood and related products

Notes: Industry at 2-digit level. Concordance has been carried out between NIC-04 and NIC-08 2-digit categories. Ranks calculated using land values (residuals), whose calculation is described in section 3.2.

Table 2: Ranking of Services Industries based Technological Requirement of Land

Rank	Industry Description
1	Activities Auxiliary to Financial Intermediation
2	Real Estate Activities
3	Other Financial Intermediation
4	Supporting and Auxiliary Transport Activities
5	Computer and Related Activities
6	Education
7	Hotel and Restaurants
8	Health and Social Work
9	Other Business Activities
10	Recreational, Cultural and Sporting Activities
11	Activities of Religious and Other Membership Organisation
12	Other Service Activities
13	Post and Telecommunications
14	Other Land Transport
15	Renting of Machinery and Equipment without Operator and of personal goods

Notes: Industry at 2-digit level. Ranks calculated using land values, whose calculation is described in section 3.2.

Table 3: Summary Statistics

Variables	Mean	S. D.	Observations
Avg. Parcel (Agricultural Input Survey)			
Avg. Parcel Area (in Hectares)	0.77	0.69	76
Manufacturing (Annual Survey of Industries)			
Total Output (in Million Rs.)	707.5	4905.02	52842
Total Employees	292.76	534.9	52756
Age of Establishment	22.09	17.65	52842
Urban Dummy	0.57	0.5	52842
Land Value (in Million Rs.)	37.55	21.55	20
Services (NSS Service Sector Survey)			
Total Output (in Million Rs.)	2.68	78.09	30942
Total Employees	6.48	53.09	30939
Urban Dummy	0.71	0.46	30942
Land Value (in Million Rs.)	7.21	10.14	15

Notes: The summary statistics are calculated from the survey years 2001-02, 2006-07, 2011-12 and 2016-17. The values of total output, total employment and land values are winsorized at 1^{st} percentile and 99^{th} percentile, respectively.

Table 4: Main Result: Output

VARIABLES	(1) ln(Output)	(2) ln(Output)
Avg parcel x Land value	0.0104***	0.00814***
	(0.00267)	(0.00226)
Observations	52,842	52,842
R-squared	0.955	0.956
Firm FE	YES	YES
State x Year FE	YES	YES
Ind x Year FE	NO	YES
Age Control	YES	YES
Industries in Sample	All 20	All 20
Wild Cluster Bootstrap p-value	0.0240	0.0050

Notes: *** p<0.01, ** p<0.05, * p<0.1. All columns report estimates from equation (1). Firm level data is from ASI 2001-02, 2006-07, 2011-12 and 2016-17. Land values (residuals) are measured in millions Rs. Standard errors are clustered at state level. p-value for δ generated using Wild Cluster Bootstrap procedure is reported.

Table 5: Main Result: Employment

VARIABLES	(1) ln(Emp)	(2) ln(Emp)	(3) ln(Emp)	(4) ln(Emp)
Avg parcel x Land value	0.00335	0.0122***	0.00240	0.00686***
	(0.00333)	(0.00252)	(0.00252)	(0.00190)
Observations	60,786	42,578	60,786	42,578
R-squared	0.935	0.935	0.936	0.935
Firm FE	YES	YES	YES	YES
State x Year FE	YES	YES	YES	YES
Ind x Year FE	NO	YES	NO	YES
Age Control	YES	YES	YES	YES
Industries in Sample	All 20	Top 10	All 20	Top 10
Wild Cluster Bootstrap p-value	0.4334	0.0230	0.4364	0.0070

Notes: *** p<0.01, ** p<0.05, * p<0.1. All columns report estimates from equation (1). Columns 1 and 3 include all 20 industries in the sample. Columns 2 and 4 include top 10 industries (based on land values) in the sample. Firm level data is from ASI 2001-02, 2006-07, 2011-12 and 2016-17. Land values (residuals) are measured in millions Rs. Standard errors are clustered at state level. p-value for δ generated using Wild Cluster Bootstrap procedure is reported.

Table 6: Heterogeneity: Age of Plants

VARIABLES	(1) ln(Output)	(2) ln(Emp)	(3) ln(Output)	(4) ln(Emp)
Avg parcel x Land value	0.00747**	0.00489**	0.0149***	0.0114*
	(0.00273)	(0.00232)	(0.00366)	(0.00577)
Observations	28,582	22,582	14,073	11,812
R-squared	0.966	0.952	0.954	0.933
Firm FE	YES	YES	YES	YES
State x Year FE	YES	YES	YES	YES
Ind x Year FE	YES	YES	YES	YES
Age Control	YES	YES	YES	YES
Industries in Sample	All 20	Top 10	All 20	Top 10
Age Sample	OLD	OLD	YOUNG	YOUNG
Wild Cluster Bootstrap p-value	0.1041	0.1582	0.0110	0.0941

Notes: *** p<0.01, ** p<0.05, * p<0.1. All columns report estimates from equation (1). Sample for columns 1 and 2 include all the firms with above median age in the industry-year cell. Sample for columns 3 and 4 include all the firms with below median age in the industry-year cell. Land values (residuals) are measured in millions Rs. Standard errors are clustered at state level. p-value for δ generated using Wild Cluster Bootstrap procedure is reported.

Table 7: Heterogeneity: Land Requirement of Industries

VARIABLES	(1) ln(Output)	(2) ln(Emp)	(3) ln(Output)	(4) ln(Emp)
Avg parcel x Land value	0.0122**	0.00686***	0.00751	-0.00464
	(0.00473)	(0.00190)	(0.0111)	(0.00861)
Observations	37,011	42,578	15,831	18,208
R-squared	0.958	0.935	0.951	0.936
Firm FE	YES	YES	YES	YES
State x Year FE	YES	YES	YES	YES
Ind x Year FE	YES	YES	YES	YES
Age Control	YES	YES	YES	YES
Industries in Sample	Top 10	Top 10	Bottom 10	Bottom 10
Wild Cluster Bootstrap p-value	0.0110	0.0070	0.5556	0.6336

Notes: *** p<0.01, ** p<0.05, * p<0.1. All columns report estimates from equation (1). Sample for columns 1 and 2 include industries with top 10 land values. Sample for columns 3 and 4 include industries with bottom 10 land values. Land values (residuals) are measured in millions Rs. Standard errors are clustered at state level. p-value for δ generated using Wild Cluster Bootstrap procedure is reported.

Table 8: Heterogeneity: Ownership of Plants

VARIABLES	(1) ln(Output)	(2) ln(Emp)	(3) ln(Output)	(4) ln(Emp)
Avg parcel x Land value	0.00821***	0.00688***	0.0685	0.00789
	(0.00237)	(0.00205)	(0.0450)	(0.0137)
Observations	51,685	41,508	1,204	1,192
R-squared	0.956	0.936	0.961	0.947
Firm FE	YES	YES	YES	YES
State x Year FE	YES	YES	YES	YES
Ind x Year FE	YES	YES	YES	YES
Age Control	YES	YES	YES	YES
Ownership	Pvt.	Pvt.	Public	Public
Industries in Sample	All 20	Top 10	All 20	Top 10
Wild Cluster Bootstrap p-value	0.0050	0.0090	0.2442	0.5405

Notes: *** p<0.01, ** p<0.05, * p<0.1. All columns report estimates from equation (1). Sample for columns 1 and 2 include all privately owned firms. Sample for columns 3 and 4 include all publicly owned firms. Land values (residuals) are measured in millions Rs. Standard errors are clustered at state level. p-value for δ generated using Wild Cluster Bootstrap procedure is reported.

Table 9: Other Outcomes

VARIABLES	(1) Plant Entry	(2) ln(Output/Emp)
Avg parcel x Land value	0.387**	0.00399**
	(0.146)	(0.00174)
Observations	1,226	52,979
R-squared	0.913	0.909
Firm FE	NO	YES
State x Year FE	YES	YES
Ind x Year FE	YES	YES
State x Ind FE	YES	NO
Industries in Sample	All 20	All 20
Wild Cluster Bootstrap p-value	0.0521	0.0991

Notes: *** p<0.01, ** p<0.05, * p<0.1. Column 1 report estimate from equation (3) and column 2 from equation (1). Plant entry denotes number of plants entered in a year in a state-industry cell. ln(Output/Emp) denote labor productivity of plants. Land values (residuals) are measured in millions Rs. Standard errors are clustered at state level. p-value for δ generated using Wild Cluster Bootstrap procedure is reported.

Table 10: Robustness to Additional Controls: Output

VARIABLES	(1) ln(Outpt.)	(2) ln(Outpt.)	(3) ln(Outpt.)	(4) ln(Outpt.)	(5) ln(Outpt.)	(6) ln(Outpt.)
Avg parcel$_{st}$ x Land value$_j$	0.00814***	0.00811***	0.00801***	0.00710***	0.00785***	0.00789***
	(0.00226)	(0.00227)	(0.00278)	(0.00247)	(0.00204)	(0.00216)
Avg Parcel$_{st}$ x Lab. Intensity$_j$		0.437				
		(0.999)				
Avg Parcel$_{st}$ x Cap. Intensity$_j$			0.0105			
			(0.0901)			
Per Capita Income$_{st}$ x Land Value$_j$				1.01e-13*		
				(5.46e-14)		
Literacy$_{st}$ x Land Value$_j$					-1.61e-10	
					(3.43e-10)	
Agri. Share$_{st}$ x Land Value$_j$						2.73e-10
						(3.70e-10)
Observations	52,842	52,838	52,838	52,842	52,842	52,842
R-squared	0.956	0.956	0.956	0.956	0.956	0.956
Firm FE	YES	YES	YES	YES	YES	YES
State x Year FE	YES	YES	YES	YES	YES	YES
Ind x Year FE	YES	YES	YES	YES	YES	YES
Age Control	YES	YES	YES	YES	YES	YES
Industries in Sample	All 20	All 20	All 20	All 20	All 20	All 20
Wild Cluster Bootstrap p-value	0.0050	0.0050	0.0080	0.0531	0.0050	0.0030

Notes: *** p<0.01, ** p<0.05, * p<0.1. All columns report estimate from equation (1). Firm level data is from ASI 2001-02, 2006-07, 2011-12 and 2016-17. Data on per capita income, literacy rate and agri. share is from Handbook of Statistics on Indian States (RBI). Land values (residuals) are measured in millions Rs. Standard errors are clustered at state level. p-value for δ generated using Wild Cluster Bootstrap procedure is reported.

Table 11: Robustness to Additional Controls: Employment

VARIABLES	(1) ln(Emp)	(2) ln(Emp)	(3) ln(Emp)	(4) ln(Emp)	(5) ln(Emp)	(6) ln(Emp)
Avg parcel$_{st}$ x Land value$_j$	0.00686***	0.00727***	0.00813***	0.00676***	0.00783***	0.00704***
	(0.00190)	(0.00227)	(0.00254)	(0.00220)	(0.00214)	(0.00205)
Avg Parcel$_{st}$ x Lab. Intensity$_j$		0.262				
		(0.791)				
Avg Parcel$_{st}$ x Cap. Intensity$_j$			-0.116			
			(0.178)			
Income Per Cap.$_{st}$ x Land Value$_j$				1.10e-14		
				(6.90e-14)		
Literacy$_{st}$ x Land Value$_j$					5.84e-10	
					(4.26e-10)	
Agri Share$_{st}$ x Land Value$_j$						-2.02e-10
						(3.50e-10)
Observations	42,578	42,578	42,578	42,578	42,578	42,578
R-squared	0.935	0.935	0.935	0.935	0.935	0.935
Firm FE	YES	YES	YES	YES	YES	YES
State x Year FE	YES	YES	YES	YES	YES	YES
Ind x Year FE	YES	YES	YES	YES	YES	YES
Age Control	YES	YES	YES	YES	YES	YES
Industries in Sample	Top 10	Top 10	Top 10	Top 10	Top 10	Top 10
Wild Cluster Bootstrap p-value	0.0070	0.0030	0.0220	0.0370	0.0040	0.0130

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. All columns report estimate from equation (1). Firm level data is from ASI 2001-02, 2006-07, 2011-12 and 2016-17. Data on per capita income, literacy rate and agri. share is from Handbook of Statistics on Indian States (RBI). Land values (residuals) are measured in millions Rs. Standard errors are clustered at state level. p-value for δ generated using Wild Cluster Bootstrap procedure is reported.

Table 12: Location of Plants across States

VARIABLES	(1) ln(Land value)	(2) ln(Land value)
Avg Parcel	0.0211*	0.00962
	(0.0113)	(0.0222)
Observations	21,842	20,558
R-squared	0.001	0.000
Includes Punjab	YES	NO
Wild Cluster p-value	0.3193	0.6937

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. All columns report estimate from equation (4). Sample for column 2 excludes plants located in Punjab. Standard errors are clustered at state level. p-value for δ generated using Wild Cluster Bootstrap procedure is reported.

Table 13: Mechanism: Effects Size Based on Age of Pending Cases Related to Land Disputes

VARIABLES	(1) ln(Output)	(2) ln(Emp)	(3) ln(Output)	(4) ln(Emp)
Avg parcel x Land value	0.0180**	0.0162***	0.00582***	0.00346
	(0.00651)	(0.00325)	(0.00176)	(0.00226)
Observations	31,383	25,356	19,461	15,727
R-squared	0.957	0.935	0.955	0.935
Firm FE	YES	YES	YES	YES
State x Year FE	YES	YES	YES	YES
Ind x Year FE	YES	YES	YES	YES
Age Control	YES	YES	YES	YES
Industries in Sample	All 20	Top 10	All 20	Top 10
Land Disputes Sample	HIGH	HIGH	LOW	LOW
Wild Cluster Bootstrap p-value	0.0898	0.0176	0.1171	0.1952

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. All columns report estimates from equation (1). Sample for columns 1 and 2 include firms located in states where age of pending cases related to land disputes is greater than its corresponding median. Sample for columns 3 and 4 include firms in states with below median case age. Land values (residuals) are measured in millions Rs. Standard errors are clustered at state level. p-value for δ generated using Wild Cluster Bootstrap procedure is reported.

Table 14: Mechanism: Effect Size Based on Land Rental Market Activity

VARIABLES	(1) ln(Output)	(2) ln(Emp)	(3) ln(Output)	(4) ln(Emp)
Avg parcel x Land value	0.0146*	0.0174***	0.00845***	0.00264
	(0.00601)	(0.00153)	(0.00196)	(0.00271)
Observations	26,722	23,094	21,032	16,017
R-squared	0.956	0.933	0.959	0.936
Firm FE	YES	YES	YES	YES
State x Year FE	YES	YES	YES	YES
Ind x Year FE	YES	YES	YES	YES
Age Control	YES	YES	YES	YES
Industries in Sample	All 20	Top 10	All 20	Top 10
State Rental Activity	LOW	LOW	HIGH	HIGH
Wild Cluster Bootstrap p-value	0.1552	0.0140	0.0340	0.3674

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. All columns report estimates from equation (1). Sample for columns 1 and 3 include firms located in states where proportion of households participating in land rental market is less than its corresponding median. Sample for columns 2 and 4 include firms in states with above median land rental market participation. Land values (residuals) are measured in millions Rs. Standard errors are clustered at state level. p-value for δ generated using Wild Cluster Bootstrap procedure is reported.

Table 15: Mechanism: Land Owned by Plants

VARIABLES	(1) ln(Land)	(2) ln(Land)
Avg parcel x Land value	0.00274	0.0115*
	(0.00580)	(0.00636)
Observations	42,522	31,440
R-squared	0.917	0.917
Firm FE	YES	YES
State x Year FE	YES	YES
Ind x Year FE	YES	YES
Age Control	YES	YES
Industries in Sample	All 20	Top 10
Wild Cluster Bootstrap p-value	0.6476	0.1792

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. All columns report estimates from equation (1). Sample for columns 1 include all 20 industries. Sample for column 2 includes top 10 industries by land values. Land values (residuals) are measured in millions Rs. Standard errors are clustered at state level. p-value for δ generated using Wild Cluster Bootstrap procedure is reported.

Table 16: Alternate Measures: Land Dummy and Land Rank

VARIABLES	(1) ln(Output)	(2) ln(Emp)	(3) ln(Output)	(4) ln(Emp)
Avg parcel x Land dummy	0.344***	0.187***		
	(0.0892)	(0.0643)		
Avg Parcel x Land Rank			0.0235***	0.0299**
			(0.00631)	(0.0124)
Observations	52,842	60,786	52,838	42,578
R-squared	0.956	0.936	0.956	0.935
Firm FE	YES	YES	YES	YES
State x Year FE	YES	YES	YES	YES
Ind x Year FE	YES	YES	YES	YES
Age Control	YES	YES	YES	YES
Industries in Sample	All 20	All 20	All 20	Top 10
Wild Cluster Bootstrap p-value	0.0020	0.0150	0.0080	0.0791

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. All columns report estimates from equation (1). Land Dummy takes 1 if industry's land value is above average, and 0 otherwise. Land Rank ranks industries in ascending order based on land values (residual). Standard errors are clustered at state level. p-value for δ generated using Wild Cluster Bootstrap procedure is reported.

Table 17: Alternate Measures: US Values

VARIABLES	(1) ln(Output)	(2) ln(Emp)	(3) ln(Output)	(4) ln(Emp)
Avg Parcel x US Land Value (in '000 $)	0.0290***	0.0215***		
	(0.00714)	(0.00553)		
Avg Parcel x US Land Dummy			0.319***	0.159**
			(0.0770)	(0.0626)
Observations	52,838	60,782	52,838	60,782
R-squared	0.956	0.936	0.956	0.936
Firm FE	YES	YES	YES	YES
State x Year FE	YES	YES	YES	YES
Ind x Year FE	YES	YES	YES	YES
Age Control	YES	YES	YES	YES
Industries in Sample	All 20	All 20	All 20	All 20
Wild Cluster Bootstrap p-value	0.0360	0.0040	0.0020	0.0450

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. All columns report estimates from equation (1). The US land value is calculated from the Annual Survey of Manufacturing (ASM) and Economic Census conducted by the US Census Bureau. US Land Dummy takes 1 if industry's land value is above average, and 0 otherwise. Standard errors are clustered at state level. p-value for δ generated using Wild Cluster Bootstrap procedure is reported.

Table 18: Robustness: Dropping plants in 90^{th}-95^{th} percentile

VARIABLES	(1) ln(Output)	(2) ln(Emp)
Avg parcel x Land value	0.00776***	0.00659***
	(0.00266)	(0.00191)
Observations	38,212	31,099
R-squared	0.951	0.923
Firm FE	YES	YES
State x Year FE	YES	YES
Ind x Year FE	YES	YES
Age Control	YES	YES
Industries in Sample	All 20	Top 10
Wild Cluster Bootstrap p-value	0.0100	0.0120

Notes: *** p<0.01, ** p<0.05, * p<0.1. All columns report estimates from equation 1. The sample in both the columns exclude firms which were in 90^{th}-95^{th} percentile of employment distribution in any of the years from 2001-02 to 2016-17. Standard errors are clustered at state level. p-value for δ generated using Wild Cluster Bootstrap procedure is reported.

Table 19: Manufacturing Main Result - Cross Section

VARIABLES	(1) ln(Output)	(2) ln(Output)	(3) ln(Emp)	(4) ln(Emp)
Avg parcel x Land value	-0.000333	0.00233	-0.000272	0.00270**
	(0.00165)	(0.00182)	(0.00117)	(0.00111)
Observations	12,578	8,865	14,343	10,086
R-squared	0.131	0.130	0.130	0.107
State FE	YES	YES	YES	YES
Ind FE	YES	YES	YES	YES
Industries in Sample	All 20	Top 10	All 20	All 20
Wild Cluster Bootstrap	0.8318	0.1361	0.7868	0.0100

Notes: *** p<0.01, ** p<0.05, * p<0.1. All columns report estimates from equation (2). Sample consists of firms from the survey year 2006-07. Standard errors are clustered at state level. Land values (residuals) are measured in millions Rs. p-value for δ generated using Wild Cluster Bootstrap procedure is reported.

Table 20: Services Sector: Main Result

VARIABLES	(1) ln(Output)	(2) ln(Output)	(3) ln(Emp)	(4) ln(Emp)
Avg Parcel x Land Values	-0.00672	-0.00487	-0.00244	-0.00247
	(0.0102)	(0.0118)	(0.00209)	(0.00277)
Observations	30,942	18,368	30,982	18,399
R-squared	0.161	0.072	0.191	0.128
State FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Industries in Sample	All 15	Top 8	All 15	Top 8
Wild Cluster Bootstrap	0.7718	0.8398	0.3253	0.4074

Notes: *** p<0.01, ** p<0.05, * p<0.1. All columns report estimates from equation (2). Sample consists of firms from Service Sector Survey 2006-07. Land values are measured in millions Rs. Standard errors are clustered at state level. p-value for δ generated using Wild Cluster Bootstrap procedure is reported.

Table 21: Services sector: Restricting to big firms within industries

VARIABLES	(1) ln(Output)	(2) ln(Output)	(3) ln(Emp)	(4) ln(Emp)
Avg Parcel x Land Values	-0.0102	-0.00753	-0.00497*	-0.00371
	(0.0144)	(0.0145)	(0.00280)	(0.00238)
Observations	19,498	9,729	19,515	9,745
R-squared	0.297	0.107	0.468	0.241
State FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Industries in Sample	All 15	Top 8	All 15	Top 8
Wild Cluster Bootstrap	0.7307	0.7608	0.1421	0.2603

Notes: *** p<0.01, ** p<0.05, * p<0.1. All columns report estimates from equation (2). Data is from Service Sector Survey 2006-07. Sample for this table excludes firms whose employment size is below median employment size of the industry. Land values are measured in millions Rs. Standard errors are clustered at state level. p-value for δ generated using Wild Cluster Bootstrap procedure is reported.

Table 22: Services: Land Dummy

VARIABLES	(1) ln(Output)	(2) ln(Emp)
Avg Parcel x Land Dummy	-0.0476	-0.0459
	(0.183)	(0.0488)
Observations	30,942	30,982
R-squared	0.161	0.191
State FE	YES	YES
Industry FE	YES	YES
Industries in Sample	All 15	All 15
Wild Cluster Bootstrap p-value	0.8999	0.3984

Notes: *** p<0.01, ** p<0.05, * p<0.1. All columns report estimates from equation (2). Data is from Service Sector Survey 2006-07. Land Dummy takes value 1 if industry's land value is greater than the average land value, 0 otherwise. Standard errors are clustered at state level. p-value for δ generated using Wild Cluster Bootstrap procedure is reported.

Table 23: Services Result: Land Rank

VARIABLES	(1) ln(Output)	(2) ln(Output)	(3) ln(Emp)	(4) ln(Emp)
Avg Parcel x Land Rank	-0.00740	0.00613	-0.00142	-0.00187
	(0.0136)	(0.0429)	(0.00374)	(0.0140)
Observations	30,942	18,368	30,982	18,399
R-squared	0.161	0.072	0.191	0.128
State FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Industries in Sample	All 15	Top 8	All 15	Top 8
Wild Cluster Bootstrap	0.6076	0.8899	0.7267	0.8488

Notes: *** p<0.01, ** p<0.05, * p<0.1. All columns report estimates from equation (2). Data is from Service Sector Survey 2006-07. Land Rank variable ranks industries in ascending order based on their land values. Standard errors are clustered at state level. p-value for δ generated using Wild Cluster Bootstrap procedure is reported.

Table 24: Services: Dropping Firms in 90^{th}-95^{th} Percentile

VARIABLES	(1) ln(Output)	(2) ln(Output)	(3) ln(Emp)	(4) ln(Emp)
Avg Parcel x Land Values	-0.00612	-0.00442	-0.00230	-0.00239
	(0.00903)	(0.0106)	(0.00171)	(0.00244)
Observations	30,240	17,877	30,279	17,907
R-squared	0.162	0.074	0.186	0.125
State FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Industries in Sample	All 15	Top 8	All 15	Top 8
Wild Cluster Bootstrap	0.7588	0.8448	0.2492	0.3393

Notes: *** p<0.01, ** p<0.05, * p<0.1. All columns report estimates from equation (2). Data is from Services Sector Survey 2006-07. The sample in both the columns exclude firms which were in 90^{th}-95^{th} percentile of employment distribution. Standard errors are clustered at state level. p-value for δ generated using Wild Cluster Bootstrap procedure is reported.

Table 25: Relation between Employment Size and Land Owned

VARIABLES	(1) ln(Emp)	(2) ln(Emp)
ln(Land Value)	0.360***	0.228***
	(0.0264)	(0.0145)
Observations	10,216	17,057
R-squared	0.384	0.410
State FE	YES	YES
Ind FE	YES	YES
Industries in Sample	All 20	All 15
Sector	Mfg	Services
Wild Cluster Bootstrap p-values	0.000	0.000

Notes: *** p<0.01, ** p<0.05, * p<0.1. All columns report estimates from equation (5). Data for first column is from ASI 2006-07 and that for second column is from Service Sector Survey 2006-07. Standard errors are clustered at state level. p-value for δ generated using Wild Cluster Bootstrap procedure is reported.