Tribal Forest Rights and Firm Behavior *

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Abstract

Indigenous communities (tribes) often inhabit ecologically sensitive land without formal property rights, leaving these areas vulnerable to commercial exploitation. Whether formalizing land rights can deter encroachment remains an open question. We develop a model showing that tribal forest rights reduce *average* firm activity near tribal areas but shift the *composition* toward larger firms. This happens because land rights raise land acquisition costs while lowering land prices. Higher transaction costs constrain smaller firms, whereas large firms benefit from cheaper land and expand investment. We test these predictions using India's Forest Rights Act as a natural experiment, which granted tribal forest rights in 2008. New district-level data on deforestation permits filed by firms confirm that land demand declines in districts with high tribal forest-dependent populations, yet encroachment by large projects persists. Firm-level evidence reveals a decline in land valuation driven by falling prices, with smaller effects for large firms. Consequently, land conflicts and displacement intensify around surviving large projects. Our findings point to a re-sorting rather than retreat of development pressure, implying that land rights reforms should be complemented by compensation schemes tied to project scale, such as revenue sharing or co-ownership, alongside stronger dispute resolution systems to mitigate conflict.

Keywords: Firms, forests, tribes, land titling, development

JEL Codes: Q15, Q23, O13, D22

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"An Act to recognise and vest the forest rights and occupation in forest lands in forest dwelling Scheduled Tribes [...] who have been residing in forests for generations but whose rights could not be recorded [...] And whereas the forest rights on their ancestral lands were not adequately recognised in the consolidation of state forests in the colonial as well as in independent India, resulting in historical injustices to the forest-dwelling Scheduled Tribes and other forest dwellers who are integral to the very sustainability and survival of the forest ecosystem [...]"

— Preamble of India's Forest Rights Act, 2006

1 Introduction

For centuries, Indigenous communities have stewarded land through collective management, traditional knowledge, and sustainable practices. Colonization dismantled these systems, stripping away customary rights and exposing tribes to land grabs and commercial exploitation. In the United States, the 1887 Dawes Act fragmented tribal land into private allotments (Carlson, 1978); in Latin America, colonial land reforms favored agribusiness over Indigenous tenure (Griffiths, 2004); and in India, the British nationalized tribal-managed forests and routinely diverted them for agriculture and industry (Bandopadhyay, 2010; Saravanan, 2011). Many countries are now confronting these dark legacies, but most reforms remain piecemeal. India stands out for enacting the first nationwide tribal forestland titling law in 2008. This sweeping policy provides a rare empirical setting to investigate a central question: how do firms respond to tribal land rights, and is legal empowerment enough to shield tribal land from industrial encroachment?

These questions are policy-relevant as structural transformation unfolds across the developing world. Manufacturing growth is land-intensive, bringing firms and tribes into competition for land (Figure 1). Since 1970, nearly 40% of land conflicts with extractive industry worldwide have involved indigenous communities (Scheidel et al., 2023). And while case studies show that tribal property rights enhance tenure security and ecological outcomes (Libecap, 2009; Costello et al., 2008), it remains an open question how such protections influence firm behavior. We offer a new insight based on theory, development permits, and a novel firm-level panel: tribal land rights successfully reduce firm activity near tribal land *on average*, but shift the *composition* toward larger and more ecologically harmful firms, leading to heightened land conflicts and population displacement.

The policy in question is India's Forest Rights Act (FRA), passed in 2006 and implemented in 2008 (FRA, 2006). The FRA offers an ideal setting to study how tribal land titling affects firm behavior. First, India's 200 million forest-dependent tribal people are all eligible for FRA titles, making it the world's first nationwide tribal land titling policy.

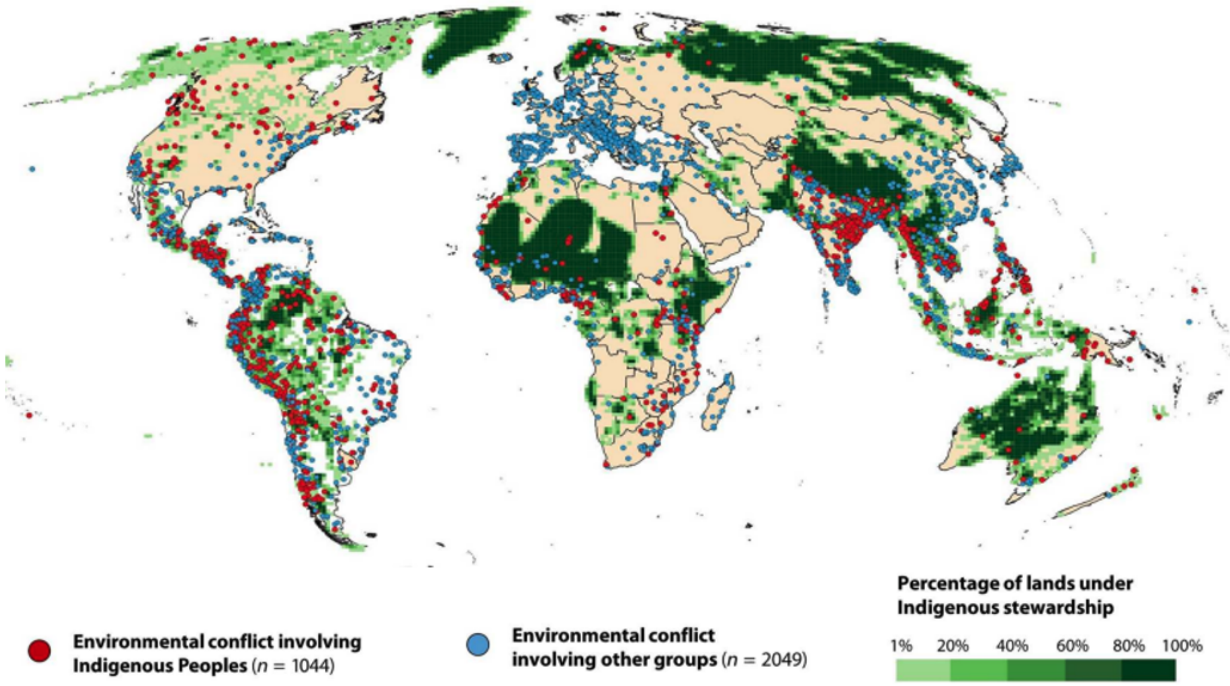

Figure 1: Land conflicts over development projects (1970-2020)
Note: Figure taken from Scheidel et al. (2023). Data obtained from the Environmental Justice Atlas.

This broad geographic scope enables a national-level characterization of firm responses, moving well beyond isolated case studies. Second, the Act formally integrates forest management rights with the law governing forest diversion by firms. Firms must obtain formal documentation of forest rights and informed consent from local communities before receiving a permit to divert forests for development, offering a rare opportunity to empirically study how such transaction costs alter firm behavior. Third, the policy applies specifically to tribes, who are spread unevenly across India's districts, enabling clear identification of treatment intensity across districts in a difference-in-difference setup.

We first propose a theoretical model of firm behavior to examine how tribal land rights affect firms' decision-making. Firms face heterogeneous land requirements for expanding into new projects. Expansion involves two costs: a market price per unit of land and an administrative cost. Under tribal land titling, firms must obtain consent from village councils, introducing a fixed cost and another size-dependent variable cost. Added costs raise the threshold productivity for new investments to be profitable. In equilibrium, aggregate land demand declines and land prices fall as marginal projects are not pursued. Yet the downward shift in land demand is not uniform: larger firms, which tend to implement larger projects on average, can spread fixed costs over larger parcels. They therefore gain more from the lower equilibrium land price. Smaller firms, on the other hand, are disproportionately constrained since the higher transaction cost negatively affects them more relative to the positive impact of the lower land price. Hence, small firms are less likely to expand firm activity post-reform, while the policy effect on large firms is more muted. The model thus predicts that tribal land rights reduce overall firm activity but shift land acquisition and other complementary firm activities toward larger firms that can better navigate the new institutional constraints.

We test the model predictions using two newly constructed administrative datasets. The first dataset measures firms' demand for land using the universe of digitized deforestation permits filed with the Indian government between 2003-2021. Permits are awarded through a mandatory ecological review required for any firm seeking to divert forestland for development projects (MoEFCC, 1980, 2003). Although permits are filed at the project level, the project location is only reported at the district level. We therefore aggregate to the number of permits filed in a district-year.

Our second dataset measures firms' operating activity using detailed accounting data. We construct an establishment-level panel of firm activity from India's Annual Survey of Industries (ASI) from 2003-2015. We obtained restricted access to an ASI version with consistent firm identifiers from the Ministry of Statistics and Programme Implementation (MoSPI). A caveat is that it does not include district identifiers; we therefore mapped firms to districts using publicly available data obtained separately. The result is one of the first ASI panels with consistent firm and district identifiers, enabling us to study within-firm changes in land use across space and time.[1] Unlike many other firm datasets, our panel is especially ideal for testing the model, as the ASI decomposes landholdings into opening value, closing value, revaluation, and additions, allowing us to observe whether increases in land valuation is from new land purchases or revaluation of the opening stock.

We use a difference-in-differences design with continuous treatment to estimate the impact of tribal forest rights on firm behavior. Across both datasets, identification relies on comparing firm activity in districts more and less exposed to the FRA, before and after the legislation was enacted. Since the FRA applies only to tribal people managing forests, we measure treatment exposure by districts' tribal population share living within 1km of the forest. The key empirical challenge is that forest-dependent tribal populations and overall tribal populations are correlated, and tribal and non-tribal districts systematically differ in other ways that may affect firms. We thus control for the interaction between overall tribal population share and an indicator of post-reform period in all our regressions, which ensures comparisons are made between similarly tribal districts, exploiting differences in forest-dependency for identifying treatment effects.

To test whether large firms are more resilient to the policy, as predicted by the model,

[1] To our knowledge, Martin et al. (2017) is the only other paper that have performed the same mapping.

we extend our research design to triple differences. In the permitting data, we classify development projects into small, medium, and large categories based on mean land area of the project sector.[2] In the ASI panel, we define large firms as having above-median landholdings. The triple differences design then compares firm behavior in treated and control districts before and after the FRA across firm size.

Difference-in-difference estimates from both datasets paint a nuanced picture of firm behavior in line with the model: tribal land rights reduce *average* firm activity, but shift the *composition* toward larger firms. Starting with results from our district-level measure of land demand, firms in districts with 1 percentage point (pp.) higher forest-dependent tribal population file 0.19 pp. fewer deforestation permits after the FRA compared to firms in control districts. Triple difference estimates reveal sharp heterogeneity by firm size: land demand falls among small firms, whereas medium and large firms are relatively unaffected, consistent with the model's prediction that land acquisition costs disproportionately constrain smaller firms. Thus, even as average land diversion declines after the FRA is passed, large projects continue to encroach on tribal-managed forests.

Our firm-level estimates corroborate and extend our findings from the permit data. First, formalizing tribal land rights reduces firms' land valuation: in districts home to larger forest-dependent tribal populations, the value of firms' landholdings is 0.3 pp. lower after the FRA. The FRA also reduces firms' capital and labour investments, reflecting complementarity of inputs. Output also declines, though estimates are imprecise.

Second, triple difference estimates show that larger firms better withstand the FRA; their contraction in land value is less than half that of smaller firms. We also find that large firms continue to purchase land after the policy.

Third, our estimates reflect within-firm behavioral changes and are uncontaminated by firms relocating across districts to evade the policy. To show this, we leverage the harmonized nature of our firm panel, where changes in district identifiers over time within firms signal cross-district moves. We find no evidence of such relocation after the FRA, strengthening confidence that our estimates are not upward biased by spatial spillovers.

These findings are stable under a variety of carefully designed robustness tests. Results hold under alternative treatment measures of forest dependency, when accounting for sector-specific business cycles, and when controlling for firm exit year, suggesting that unobserved factors driving firm exit are not biasing our estimates. Most importantly, our findings are validated by satellite forest imagery, which yields the same average-versus-compositional distinction observed in permit and firm-level data. While deforestation declines on average, forest loss intensifies in districts with larger projects. This robustness

[2] Project size categories are as follows. Large firms: defense, mining; medium: irrigation, electricity, other; small: transportation, services and underground.

exercise strengthens internal validity by showing that our findings from administrative data are echoed in independent satellite imagery.

The paper concludes with an analysis of land conflict and population displacement, which are informative about tribal welfare. The change in the level and composition of firm activity due to the FRA has ambiguous welfare effects: while the decline in average firm activity may raise tribal welfare, the shift toward larger firms may reduce welfare. In the absence of direct welfare data, we obtained a novel dataset on land conflicts through a private agency that tracks land disputes reported in the Indian media. Using our difference-in-differences framework, we find that, despite the decline in average firm activity, land conflicts and population displacement intensify around surviving large projects. This suggests that welfare losses associated with large-scale forest diversion more than offset any welfare gains from reduced average firm activity.

Taken together, our findings paint a picture of re-sorting rather than a retreat of development pressure on tribal land. The change in industry composition toward larger firms suggests that land rights reforms should be complemented by compensation schemes tied to project scale, such as revenue sharing or co-ownership, so that affected communities share in rents generated by large projects. Moreover, stronger dispute resolution systems are needed to mitigate land conflict.

Literature Contributions This paper contributes to three literatures on tribal property rights, firm responses to environmental policy, and land reform. Our primary contribution is to provide the first evidence that tribal land titling protects land from commercial interests using firm-level data for an entire country. This speaks to foundational debates on whether private property rights can solve the "tragedy of the commons" and improve natural resource governance (Coase, 1960; Ostrom, 1990; Hardin, 1968). While existing studies show that property rights over natural resources improve ecological outcomes (Libecap, 2009; Costello et al., 2008; Romero and Saavedra, 2021; Abman and Carney, 2020; Chhatre and Agrawal, 2008), we uncover a novel mechanism: conservation gains arise partly because tenure security lowers land encroachment by developers.

Second, we advance a small but growing body of work within the property rights literature on the restoration of Indigenous property rights. Prior work from the U.S., Peru, and Chile—often limited to specific tribes or sub-national regions—yield mixed results (Jordan and Heilmayr, 2025; Sanchez et al., 2023; Blackman et al., 2017; Robinson et al., 2017). We expand this literature by credibly evaluating one of the first national-scale tribal land titling policies in India which covers 200 million people. A notable exception is Nandwani (2022), which shows that the FRA increases land conflicts[3]. We deepen their

[3] Another related paper is Madhok (2023), which shows that biodiversity loss from infrastructure devel-

analysis with firm-level data and uncover a key mechanism: conflict rises because large firms are resilient to the FRA and continue to disrupt local livelihoods.

Third, we contribute to the literature on environmental regulation and firm performance. Existing work largely focuses on air and water regulation in high-income countries (Dechezleprêtre and Sato, 2017; Cohen and Tubb, 2018; Greenstone, 2002; Greenstone et al., 2012; List et al., 2003), with less attention on firm responses to land policy. Even within the small literature on environmental policy and firms in developing countries, land regulation remains understudied (Lu and Pless, 2024; Duflo et al., 2013; He et al., 2020; Kala et al., 2025; Gechter and Kala, 2025). This is a crucial knowledge gap given that structural change is intensifying land pressure across the developing world. We help fill this gap by studying firm-level impacts of land titling in India.

A closely related paper is Kala et al. (2025), which shows that reducing the environmental permitting burden in India increases firm entry, especially among small firms. We advance their work by documenting the mirror image from an opposite policy that *raises* regulatory burden, showing that it disproportionately constrains small firms. We also examine the intensive margin instead, documenting effects on expansion conditional on entry. Lastly, we link changes in industry composition to land conflict, showing how permitting shapes not just firm activity but also local welfare.

The next section provides background on tribal forest rights. Section 3 presents a model of firm behavior to guide our empirical strategy. Section 4 describes the land permit and firm panel data, and Section 5 outlines the research design. Section 6 presents estimates of the impact of tribal forest rights on firm behavior. Section 7 discusses implications for land conflict between developers and tribes. Section 8 concludes.

2 The Forest Rights Act

India's landmark Forest Rights Act (FRA), officially titled *The Scheduled Tribes and Other Traditional Forest Dwellers (Recognition of Forest Rights) Act*, was implemented in 2008 to rectify the historic exclusion of its tribal population from formal land titling (FRA, 2006). The Act grants tribes the right to inhabit and cultivate forestland, collect forest produce, and, crucially for this paper, the right to informed consent with developers seeking to divert forestland for development projects. Below, we discuss the genesis of the FRA, its objectives, and implications for tribes and firms.

India's tribes comprise nearly 10% of the population and are characterized by higher levels of poverty and a deep dependence on forests for their livelihoods. For centuries, tribes exercised de facto control over forestland (Figure 2). This changed under British

opment is smaller in districts that are more inclusive of tribal communities.

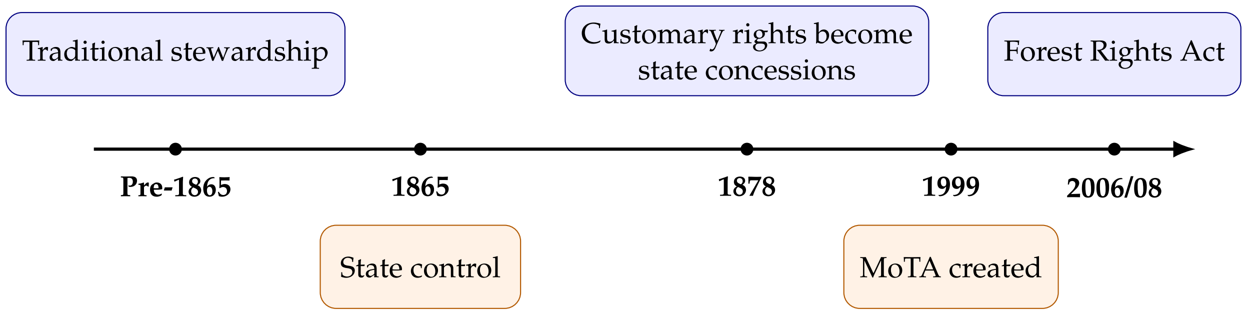

Figure 2: Timeline of India's Forest Policy

rule: the 1865 Forest Act marked the start of state appropriation, followed by an 1878 amendment which redefined customary rights as state-granted concessions (Roy and Mukherjee, 2008). This effectively criminalized tribal presence on ancestral lands. Moreover, the broad goal of bringing forestland under state control was to exploit them for commercial purposes. As B. Ribbentrop wrote in his book *Forestry in British India* in 1900: "[...] forests were considered as an obstruction to agriculture rather than otherwise, and consequently a bar to the prosperity of the Empire." (Quote from Bandopadhyay (2010))

Post-independence forest policy largely upheld this extractive model, enshrining state control and industrial access over traditional land rights. After a century of tribal exclusion from forest policy, mounting civil society pressure led to the creation of the Ministry of Tribal Affairs in 1999, which drafted the FRA in 2006 and oversaw its implementation in 2008. The objective of the FRA is to restore forest management to tribes through three key provisions: (i) *individual forest rights* to inhabit and cultivate forestland, (ii) *community land rights* to access and use forest produce, and (iii) *community forest rights* to conserve, protect, and manage forestland (FRA, 2006).

The process of formalizing these rights is hierarchical. Applications are first vetted by village councils, followed by verifications at sub-divisional and district committees, and finally receiving approval from a state committee. These are slow processes, often involving multiple verifications and objections at each level, resulting in back-and-forth of applications and imperfect allocation of rights in a given community at any time.

A key by-product of this formalization exercise is its implication for protecting traditional forestland from acquisition by firms—the central focus of this paper. Before the FRA, firms seeking to divert forestland for development could obtain permission under the Forest (Conservation) Act (1980) subject to an environmental review (MoEFCC, 1980). The process originally involved only state agencies, effectively ignoring tribal claims to the earmarked forestland. After the FRA, however, the permitting process was amended to require informed consent by the local community through a public meeting called by the village council, known as the Gram Sabha[4]. As part of the land acquisition process, firms now must submit the following documents with their development proposal:

- Certification that forest rights under the FRA have been identified and settled. See Figure B1 for an example certification letter.
- Proof that project details were presented to Gram Sabhas in the local language.
- Written resolutions from each Gram Sabha approving or rejecting the proposal, including any compensatory or ameliorative measures negotiated.
- Evidence that consultations were held with at least 50% quorum[5].

These four provisions formally embed community participation into the permitting process. Yet from firms' perspective, the integration of the FRA into the Forest (Conservation) Act introduces a transaction cost: they must obtain the necessary documentation about the transfer of rights to the local community and secure meaningful consent from them, not just navigate state bureaucracy. While one may conclude that this would deter firms away from tribal forestland, we argue that the (relative) cost of this process is not uniform. Instead, the transaction cost disproportionately affects smaller firms, for whom the additional administrative work is more binding. This leads to an equilibrium where the FRA reduces firm activity on average, but shifts the *composition* toward larger firms. Next, we formalize this intuition with a model of firm behavior with transaction costs.

3 Model

3.1 Set-up

Consider a firm with land size l located near forestland. The firm is contemplating whether to expand its activity by venturing into a new investment project. The new project is characterized by the vector $(\tilde{l}, \tilde{z})$, where $\tilde{l}$ is the optimal (additional) land requirement for the project and $\tilde{z}$ is the unobservable productivity of the project. If implemented, real output generated from the project is given by $Q(\tilde{l}, \tilde{z}) = \tilde{z}q(\tilde{l})$, where $q(\tilde{l})$ is strictly increasing and strictly concave in $\tilde{l}$.[6]

[4]Chapter II Section M of the FRA states that diversion of forestland under the Forest (Conservation) Act is allowed if "the clearance of such developmental projects [...] is recommended by the Gram Sabha" (p.5).

[5]Letter F. No. 11-9/1998-FC (pt) by C. D. Singh, Senior Assistant Inspector-General of Forests: https://forestrightsact.com/wp-content/uploads/2016/04/moef_circular_on_diversion_fra.pdf.

[6]Output is produced using labor and capital deployed on the new project, i.e., input usage is complementary to land acquisition. The function $q()$ subsumes the optimal input levels deployed. We examine input usage empirically to show consistent results (Section 6.2.4).

Project size, $\tilde{l}$, and productivity, $\tilde{z}$, are drawn independently from two distributions. The project size distribution depends on the initial land size of the firm. We assume that $\tilde{l} \sim G_l$ such that $l > l'$ implies $G_l(\tilde{l}) < G_{l'}(\tilde{l})$ for all $\tilde{l} > 0$. Therefore, firms with larger initial land size are more likely to invest in larger projects than firms with smaller initial landholdings. At the extremes, $\lim_{l \to 0} G_l(\tilde{l}) = 1$ for any $\tilde{l} \in (0, \infty)$ and $\lim_{l \to \infty} G_l(\tilde{l}) = 0$ for any $\tilde{l} \in (0, \infty)$, implying that very small firms almost surely draw negligible expansion opportunities whereas very large firms almost surely invest in very large projects.

Let project productivity $\tilde{z} \sim F(\tilde{z})$ be drawn independently of $\tilde{l}$. The firm owner must purchase the land and bear any administrative costs of securing approvals from the relevant Ministry to implement the project. Let p be the real land price and $c(\tilde{l})$ be the administrative cost of seeking approval, where $c'(\tilde{l}) > 0$ and $c''(\tilde{l}) \geq 0$. The firm implements the project if and only if:

$$\tilde{z}q(\tilde{l}) \;\geq\; p\tilde{l} + c(\tilde{l})$$

$$\text{or, } \tilde{z} \;\geq\; \frac{p\tilde{l} + c(\tilde{l})}{q(\tilde{l})} \;=\; z^*(\tilde{l}, p)$$

where $z^*(\tilde{l}, p)$ is the threshold productivity level above which the firm proceeds with the project of size $\tilde{l}$. For expansion opportunity $\tilde{l}$, the likelihood of expansion is thus given by $[1 - F(z^*(\tilde{l}, p))]$. The firm's overall probability of expansion can be written as:

$$\psi(l, p) = \int_0^\infty \left[1 - F\left(z^*(\tilde{l}, p)\right)\right] dG_l(\tilde{l})$$

3.2 Land Market Equilibrium

The expected demand for land by the firm equals the size of each potential project weighted by its probability of implementation:

$$D_l(p) = \int_0^\infty \tilde{l}\left[1 - F\left(z^*(\tilde{l}, p)\right)\right] dG_l(\tilde{l}) \tag{1}$$

For each $\tilde{l}$, $z^*(\tilde{l}, p)$ is strictly increasing in p. Therefore, $D_l(p)$ is strictly falling in p. The aggregate land demand in the market is given by:

$$D(p) = \int_0^\infty D_l(p) d\Theta(l) \tag{2}$$

where $\Theta(l)$ is the CDF of the firm land size distribution in the market. Since $D_l(p)$ is decreasing in p for all l, aggregate demand $D(p)$ is also strictly decreasing. Let $S(p)$ denote aggregate land supplied at price p. We assume $S(p)$ is strictly increasing in p and

$S(0) = 0$, as in any standard model. Equilibrium land price, p^*, is therefore given by:

$$D(p^*) \ = \ S(p^*)$$

Clearly, p^* exists and is unique. Existence follows from $D(0) > 0$ and $\lim_{p \to \infty} D(p) = 0$. Uniqueness follows from strict monotonicity of demand and supply.

3.3 Introduction of Forest Rights Act

The FRA requires that each project acquire additional documentation regarding local community's rights over the forestland and receive consent from them before it can be established. We model this as an increase in the transaction cost of project implementation, given by $\kappa(\tilde{l}) > 0$ where $\kappa(\tilde{l}) = \kappa_0 + \kappa_1 \tilde{l}$ with $\kappa_0, \kappa_1 > 0$. The parameter κ_0 is a fixed cost of the land transaction, since FRA compliance is required for any amount of land purchase. The term κ_1 captures scale-dependent transaction costs: larger land purchases require approval from potentially multiple villages and entail greater coordination costs. The new threshold productivity becomes:

$$z^{**}(\tilde{l}, p) = \frac{p\tilde{l} + c(\tilde{l}) + \kappa(\tilde{l})}{q(\tilde{l})} \ > \ z^*(\tilde{l}, p)$$

Given this new threshold, the firm's expansion probability at any price p is now:

$$\psi^{FRA}(l, p) = \int_0^\infty \left[1 - F\left(z^{**}(\tilde{l}, p)\right)\right] dG_l(\tilde{l}) \ < \ \psi(l, p)$$

The demand for land by firm of size l in the presence of FRA then becomes:

$$D_l^{FRA}(p) = \int_0^\infty \tilde{l}\left[1 - F\left(z^{**}(\tilde{l}, p)\right)\right] dG_l(\tilde{l}) \ < \ D_l(p)$$

$$\Rightarrow D^{FRA}(p) = \int_0^\infty D_l(p) d\Theta(l) \ < \ D(p)$$

Hence, the FRA causes the market land demand curve to shift left.

3.3.1 Effect on Demand for forestland

Let the new equilibrium price be p^{**}. Clearly, $p^{**} < p^*$, which gives the result:

Result 1 *Aggregate demand for land deforested falls due to FRA, i.e., $D^{FRA}(p^{**}) \ < \ D(p^*)$.*

We thus expect a fall in overall demand for deforestation owing to a fall in firms' demand for land in FRA-affected regions. However, the impact on demand is heterogeneous across large and small firms. To see this, we compare the threshold productivity at the two equilibria. It is easy to check that:

$$z^{**}(\tilde{l}, p^{**}) > z^{*}(\tilde{l}, p^{*}) \quad \text{if } \tilde{l} < \hat{l}$$
$$z^{**}(\tilde{l}, p^{**}) < z^{*}(\tilde{l}, p^{*}) \quad \text{if } \tilde{l} > \hat{l} \tag{3}$$

where $\hat{l} = \frac{\kappa_0}{(p^* - p^{**}) - \kappa_1}$.[7] The productivity threshold increases for smaller projects and decreases for larger projects due to the FRA. The change in the demand for deforestation for a firm with size l can be written as:

$$\Delta D(l) = D_l^{FRA}(p^{**}) - D_l(p^*) = \int_0^{\hat{l}} \tilde{l} \left[F\left(z^*(\tilde{l}, p^*)\right) - F\left(z^{**}(\tilde{l}, p^{**})\right)\right] dG_l(\tilde{l})$$
$$+ \int_{\hat{l}}^{\infty} \tilde{l} \left[F\left(z^*(\tilde{l}, p^*)\right) - F\left(z^{**}(\tilde{l}, p^{**})\right)\right] dG_l(\tilde{l})$$

By Equation (3), the first RHS term is negative and the second term is positive. Under our assumptions about $G_l(\cdot)$, if l is small enough, then the first (negative) term dominates, such that $\lim_{l \to 0} \Delta D(l) < 0$. Moreover, as l increases, the weight of the first (negative) term falls and that of the second term increases. Therefore, $\Delta D(l)$ increases with l. We collect these observations in our second theoretical result:

Result 2 *The demand for deforestation by small firms falls due to the FRA, i.e., $\Delta D(l) < 0$ for l small enough. The fall in demand is smaller for larger firms, i.e.,*

$$\frac{\partial \Delta D(l)}{\partial l} > 0$$

Intuitively, the aggregate fall in demand for forestland is driven mainly by small firms, which are disproportionately affected by the FRA. Large firms, which have greater demand for forestland, experience a more muted response. This highlights a potential trade-off with conservation legislation: while it reduces aggregate deforestation (Result 1), it imposes heterogeneous economic costs on firms. For larger firms, the increased transaction cost due to the FRA is offset by the lower price of land. For smaller firms, the transaction cost is higher (per unit of land) relative to the fall in price. Consequently, the demand effect is stronger for them. As the next set of results show, the legislation consequently changes the composition of economic activity in favor of larger firms.

[7] We assume that $\kappa_1 < (p^* - p^{**})$, i.e., marginal increase in transaction cost due to higher land purchase is lower than marginal fall in land value due to FRA. Otherwise, $\hat{\hat{l}} = 0$.

3.3.2 Effect on Firms' Land Expansion Likelihood

We now examine how the equilibrium effect on the land market generates heterogeneous effects for firms' land acquisition behavior. The FRA reduces the implementation probability for small projects by increasing their threshold productivity (Equation 3), whereas the implementation probability increases for larger projects. The impact of the FRA on the overall expansion probability for a firm of size l is therefore given by:

$$\Delta\psi(l) \equiv \psi^{FRA}(l, p^{**}) - \psi(l, p^*) = \int_0^{\hat{l}} \left[F\left(z^*(\tilde{l}, p^*)\right) - F\left(z^{**}(\tilde{l}, p^{**})\right)\right] dG_l(\tilde{l}) + \int_{\hat{l}}^{\infty} \left[F\left(z^*(\tilde{l}, p^*)\right) - F\left(z^{**}(\tilde{l}, p^{**})\right)\right] dG_l(\tilde{l})$$

Following identical logic as before, if l is small enough, the first term dominates the second term, i.e., $\lim_{l\to 0} \Delta\psi(l) < 0$. Additionally, $\Delta\psi(l)$ is increasing in l, which gives:

Result 3 *The probability of expansion or new land purchase will fall due to FRA for small firms, i.e., $\Delta\psi(l) < 0$ for l small enough. Additionally, $\Delta\psi(l)$ increase with l, i.e., $\frac{\partial\Delta\psi(l)}{\partial l} > 0$*

If firms' land size is very large, the expansion probability can increase as well. The average probability of land purchase in the market is given by:

$$\Delta\Psi = \int_0^{\infty} \Delta\psi(l) d\Theta(l)$$

which can be either positive or negative depending on the nature of the distribution of initial land size in the market.

3.3.3 Effect on Firms' Land Valuation

The land valuation of a firm pre-FRA is $V(l) = p^*(l + D_l(p^*))$, and post-FRA is $V^{FRA}(l) = p^{**}(l + D_l^{FRA}(p^{**}))$. The overall impact of the FRA on firms' land valuation is therefore:

$$\begin{aligned}\Delta V(l) &= (p^{**} - p^*)l + (p^{**} D_l^{FRA}(p^{**}) - p^* D_l(p^*)) \\ &= (p^{**} - p^*)(l + D_l^{FRA}(p^{**})) + p^* \Delta D(l)\end{aligned}$$

The first term on the RHS is negative, and the second term is negative for small l (Result 2). Hence, $\Delta V(l) < 0$ for small firms. Additionally, both $D_l^{FRA}(p^{**})$ and $\Delta D(l)$ are increasing in l. Differentiating $\Delta V(l)$ with respect to l l yields:

$$\frac{\partial \Delta V(l)}{\partial l} = (p^{**} - p^{*})(1 + D_l^{FRA'}(p^{**})) + p^{*}\Delta D^{'}(l)$$

The first term on the RHS is negative since $p^{**} < p^{*}$, while the second term is positive because $\Delta D'(l) > 0$. The overall sign therefore depends on the relative magnitudes of these two forces. If $\Delta D^{'}(l)$ is sufficiently large, i.e., if the contractionary effect of the FRA on larger firms' demand for forestland is muted, then $\frac{\partial \Delta V(l)}{\partial l} > 0$.

Result 4 *For small firms, land valuation falls, i.e., $\Delta V(l) < 0$ due to FRA. The fall in land valuation for larger firms is smaller, i.e., $\frac{\partial \Delta V(l)}{\partial l} > 0$, only when $\Delta D^{'}(l)$ is large.*

The fall in valuation *rate*, however, is uniform across firms, since all firms in a market face the same price. We collect this observation as a separate result:

Result 5 *The land reevaluation rate of firms, given by $\frac{p^{**}}{p^{*}}$ is same across firms of any size.*

3.3.4 Downstream Effects: Output and Productivity

The change in the expected output from the new project due to the FRA is given by:

$$\Delta Q(l) = \int_0^{\infty} \Delta q(\tilde{l}) dG_l(\tilde{l}) = \int_0^{\hat{l}} \Delta q(\tilde{l}) dG_l(\tilde{l}) + \int_{\hat{l}}^{\infty} \Delta q(\tilde{l}) dG_l(\tilde{l}) \tag{4}$$

$$\text{where} \;\; \Delta q(\tilde{l}) = \left\{ \int_{z^{**}(\tilde{l}, p^{**})}^{\infty} \tilde{z} dF(\tilde{z}) - \int_{z^{*}(\tilde{l}, p^{*})}^{\infty} \tilde{z} dF(\tilde{z}) \right\} q(\tilde{l})$$

Similarly, the change in expected productivity can be written as:

$$\Delta \zeta(l) = \int_0^{\hat{l}} \Delta z(\tilde{l}) dG_l(\tilde{l}) + \int_{\hat{l}}^{\infty} \Delta z(\tilde{l}) dG_l(\tilde{l}) \tag{5}$$

$$\text{where} \;\; \Delta z(\tilde{l}) = \left\{ \int_{z^{**}(\tilde{l}, p^{**})}^{\infty} \tilde{z} dF(\tilde{z}) - \int_{z^{*}(\tilde{l}, p^{*})}^{\infty} \tilde{z} dF(\tilde{z}) \right\}$$

The expression $\Delta q(\tilde{l})$ (and $\Delta z(\tilde{l})$) captures the expected change in output (and productivity) of a firm with project size $\tilde{l}$. Clearly, $\Delta q(\tilde{l}), \Delta z(\tilde{l}) < 0$ if $\tilde{l} < \hat{l}$ and $\Delta q(\tilde{l}), \Delta z(\tilde{l}) > 0$ if $\tilde{l} > \hat{l}$. Hence, the first terms in the RHS of equations (4) and (5) are negative and the second terms are positive. Using similar logic that we used for Result 2 we conclude that:

Result 6 *For small firms, the FRA reduces expected output and productivity from new projects. For larger firms, the fall in output and productivity is smaller, i.e.,* $\Delta Q(l)$ *and* $\Delta\zeta(l)$ *increase in* l.

In summary, our model delivers predictions on both the average and heterogeneous effects of the FRA on firm behavior. On average, the policy reduces firm activity. This contraction is concentrated among small firms, whereas larger firms are relatively insulated. The predictions span a range of firm outcomes—demand for forestland, probability of land expansion, land valuation, and productivity and output. Next, we take the model to the data and examine the extent to which the theoretical predictions hold in India.

4 Data

We test the model predictions by drawing on several new datasets. We build a panel of deforestation permits filed by firms between 2003-2021 to study changes in the demand for forestland near tribal land. We link this with a restricted-access firm panel spanning 2003-2015 to study changes in firm behavior. Policy exposure is measured by the tribal population share living near forests.

4.1 Demand for Forestland by Developers

Results 1 and 3 of the model show how conservation legislation changes incentives faced by developers seeking to convert forestland for industry. A key contribution of our paper is to empirically document this forest encroachment by constructing a first-of-its-kind panel of deforestation permits filed by developers. Unlike satellite forest data, permit records allow us to track forestland earmarked for diversion by industrial activity.

Permit records are held in the online PARIVESH portal[8]. Each permit describes the project category (e.g. mining, power plant), district, hectares of forest earmarked for diversion, date of submission, and date of approval. Exact project coordinates are not given, making districts the lowest location identifier. Appendix C.1 provides details on data cleaning and processing. Table A1 summarizes the permit data. There were 42,035 project permits reviewed between 2003-2021, collectively representing 1.1 million ha. of proposed deforestation. The average encroachment is 26 ha., roughly the size of 40 soccer pitches. Defence projects are the fewest in number, but largest in size. Mines are the second least common but represent 40% of total deforestation.

The final permit sample aggregates projects to the district-year level, both overall and category wise (e.g., number of deforestation permits filed for mining projects in 2015 in

[8]Data can be accessed at: www.parivesh.nic.in.

Rayagada, Odisha). The panel is balanced by zero-filling permits in districts not in the sample. This is reasonable since all projects undergo permitting, and our sample contains the universe of permit applications. District-years not in the sample, therefore, must have no developers applying for deforestation permits. Figure B2 maps the spatial distribution of deforestation permits across India. Development projects divert forests nationwide, with the West and North suffering the most encroachment.

While our permit data is well suited to characterize land demand, aggregation at the district level prevents analysis of firm behavior at finer scales. Deforestation permits also do not capture production activity, limiting our ability to assess whether conservation policy constrains firm activity near tribal land (Results 5 and 6 of the model). Next, we describe how we overcome these limitations with a detailed firm-level panel.

4.2 Firm Panel

We document how firm activity responds to conservation legislation by building a novel firm panel that harmonizes two versions of the Annual Survey of Industries (ASI), a detailed survey published by the Ministry of Statistics and Programme Implementation (MoSPI). The ASI covers all registered manufacturing firms with > 100 workers and a representative sample with smaller firms. A publicly available version consists of annual cross sections of firms with district IDs but no firm IDs. We instead obtained a restricted-access version from MoSPI with unique firm IDs but no district IDs. We created a mapping between the two versions using exact balance sheet values, yielding one of the first ASI versions with consistent firm and district identifiers[9]. Appendix C.2 provides details of the linking process. Martin et al. (2017) also use this approach and find consistent opening and closing capital stock values from year to year in the matched firm panel, demonstrating reliability of the mapping procedure.

The ASI is the best available dataset to study how firms respond to land policy in India. First, since it is a firm-level panel, the data is well-suited for studying how firms adjust over time in response to policy shocks. Second, unlike firm datasets from other countries, the ASI decomposes firms' land valuation into opening value, closing value, revaluation, addition (purchases), and deductions (sales)[10]. This allows us to distinguish whether increasing land values arise from purchases of new land, or revaluation of the opening stock. Lastly, the ASI offers broader coverage than other firm datasets in India. For instance, the Prowess panel surveys just 774 firms in 2007 (Martin et al., 2017), whereas our matched panel covers 50,000 firms in the same year.

[9]The mapping performs poorly for the years 2004 and 2009 (Appendix C.2). These years are therefore dropped in the main analysis. Results are unchanged when they are included (Section 6.2.2).

[10]Only 2% of firm-year observations record land sales.

The main outcomes are firms' land valuation, land purchases, and the revaluation rate. Land valuation is measured as the closing value of land; variation reflects either purchases of new land, or revaluation of the opening stock. Since we observe land additions separately from revaluation, we define land purchases as an indicator equal to one if land additions is positive. The revaluation rate is defined as the revaluation of the opening land stock divided by the opening value. This value proxies for land prices since it measures the proportional change in land value, holding physical land fixed.

We also measure downstream policy impacts on total factor productivity (TFP) and non-land inputs, including capital and labour. Firm-level TFP is constructed using the estimation approach in Levinsohn and Petrin (2003)[11] Capital is measured as the closing value of the capital stock. Labour is measured as number of employees. All input and output variables are winsorized at the 95th percentile to remove outliers.

The main estimation sample is an unbalanced panel of 145,711 fims spanning 2003-2015. Table A2 summarizes key outcome variables for these firms. Eight percent of firm-year observations record land purchases during the study period. About $0.42/35 \approx 1.2\%$ of firms' closing land value is comprised of new land purchases.

4.3 Policy Exposure

We measure FRA exposure by district tribal population share living within 1km of the forest edge. We refer to this variable in our regressions as *ForestPop*. The data on FRA titles held in each district is not available. Moreover, evolution of extent of FRA titling in a district would be endogenous to the local governance characteristics, which would have direct implication on firm activity in the district. Our measure instead captures potential exposure to the treatment since it incorporates both FRA eligibility criteria: tribal status and forest-dependence. We use our treatment measure to compare firm activity before and after the FRA in districts more and less exposed to the policy. We therefore interpret our results as intent-to-treat (ITT) effects.

We construct the continuous treatment in three steps. First, we obtain 2015 gridded forest cover data from the Vegetative Continuous Fields (VCF) product (Townshend et al., 2017) and clump cells with $> 40\%$ forest cover into "patches". Second, we obtain geocoded village-level tribal population from the SHRUG database (Asher et al., 2021) and compute the distance from each village to the nearest forest patch. Lastly, we aggregate tribal populations in villages within 1km of the forest edge to the district level and divide by district population. This generates a district-level measure of FRA eligibility.

[11] We use output as the dependent variable and energy inputs as the proxy. We use capital and firm age as the state variables, in line with Lu and Pless (2024).

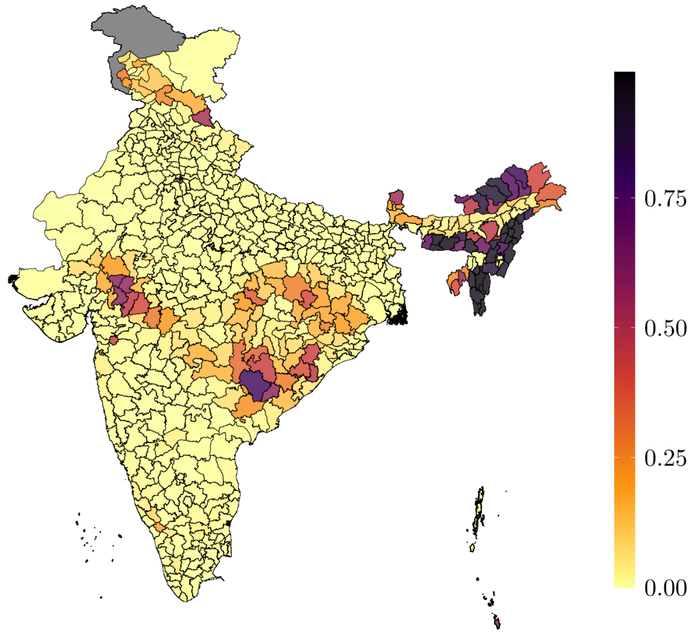

Figure 3: Treatment Variable: Tribal population share living within 1km of forest
Note: colors describe tribal population living within 1km of forest divided by total district population.

We test robustness to alternative treatment measures in Section 6.2.2 and document stable estimates under different distance-based measures of forest dependence.

Figure 3 illustrates the treatment variation. The FRA-eligible population is highest in the Northeast, home to India's hill tribes, as well as the East, known as the "tribal belt", and the lower reaches of the Himalayas. Remaining districts with near-zero forest-dependent tribal people (cream color) constitute the control group.

4.4 Covariates

The key covariate in all our regressions is district tribal population share. We include this because our treatment variable—tribal forest dependency—is correlated with total district tribal population, and tribal and non-tribal districts differ in many ways. By controlling for the tribal population share, comparisons are made between similarly tribal districts, exploiting variation in forest dependency for identification. Data on total tribal population are also from the SHRUG. Table A3 shows correlations between the two variables: on average across India, over half of districts' tribal population are forest-dependent.

Remaining covariates include temperature and rainfall, which may co-determine industrial activity as well as the distribution of tribal populations. Temperature (°C) and rainfall (mm) are from the ERA5 satellite product on a 0.125° grid (Hoffmann et al., 2019). We extract means over cells within a district and year, weighted by cell overlap fraction.

5 Empirical Strategy

This section outlines our empirical strategy to test the theoretical predictions. We exploit two sources of variation to study the impact of tribal forest rights on firm behavior: i) geographic variation in policy exposure, and ii) time variation in firm activity. We combine these sources of variation into a difference-in-difference design that compares firm behavior across FRA-exposed (treatment) and non-exposed (control) districts, before and after the policy. We also extend the framework to study heterogeneity by firm size.

5.1 Estimation Framework: Demand for Forestland

We begin by examining whether the FRA lowers firms' demand for forestland at the district level, as predicted by Result 1 from the model. The impact of the FRA on firms' demand for forestland is estimated with the following equation:

$$\begin{aligned} \text{Log } P_{dt} = \nu \cdot (ForestPop_d \cdot \mathbb{1}_{t>2007}) + \xi \cdot (TribalPop_d \cdot \mathbb{1}_{t>2007}) \\ + \mathbf{X}'_{dt}\Omega + \alpha_d + \gamma_t + \epsilon_{dt} \end{aligned} \tag{6}$$

where d and t index the district and year. The main outcome, P_{dt}, is the number of deforestation permits filed by firms in district d in year t. We also estimate versions where P_{dt} is the number of permits for each project category and size category. The treatment variable is $ForestPop_d$, the tribal population share living near forests. This enters interacted with $\mathbb{1}_{t>2007}$, a pre-post indicator that switches on in 2008 when the FRA was implemented. Importantly, we control for the interaction of overall tribal population share, $TribalPop_d$, with the pre-post dummy to disentangle the FRA from confounding differences between tribal and non-tribal areas. $\mathbf{X}_{dt}$ is a vector of covariates described in Section 4.4. All specifications include district and year fixed effects, γ_d and γ_t, respectively.

The coefficient of interest is ν. If firms earmark less forestland for development after the FRA, then $\nu < 0$ and the results align with Result 1 of the model. Because treatment is measured as a share, we estimate ν via OLS in a TWFE framework with continuous treatment (Callaway et al., 2024). In this setup, districts receive different "doses" of forest-dependent tribal populations, while others are untreated. The estimated ν recovers a weighted average of marginal treatment effects across districts and time, which can be interpreted as the average slope of the dose-response function.

While heterogeneity can be studied naively by estimating Equation 6 separately for small, medium, and large projects, we instead document heterogeneity by project size more formally using a triple difference equation. This requires reshaping the data from the district-year level to the district-year-size level. Let $j \in \{\text{s, m, l}\}$ index small, medium, and large projects based on category-wise size estimates in Table A1.[12] Letting P_{jdt} denote the number of permits filed for projects of size j in district d of year t, we estimate:

$$\text{Log } P_{jdt} = \nu \cdot (ForestPop_d \cdot \mathbb{1}_{t>2007}) + \sum_{k \in \{\text{m, l}\}} \phi_k \cdot (ForestPop_d \cdot \mathbb{1}_{t>2007} \cdot \mathbb{1}_{j=k}) \qquad (7)$$

$$+ \mathbf{X}'_{dt}\Omega + \theta_j + \alpha_d + \gamma_t + \epsilon_{jdt}$$

where $\mathbb{1}_{j=k}$ is an indicator for size category j and remaining terms are defined as in Equation 6. The explanatory variable of interest is the triple interaction term. Small projects are the omitted category, and the covariate vector, $\mathbf{X}_{dt}$, includes all lower-order interactions. Thus, ν captures the impact of the FRA on land demand for small projects, while ϕ_{med} and ϕ_{large} measure differential impacts for medium and large projects relative to small projects, respectively. Size fixed effects, θ_j, account for time-invariant unobserved heterogeneity by project size. Note that $\nu < 0$ and $\phi_{large} > 0$ implies that land demand falls for small projects, but rises for large projects, consistent with Result 3 of the model.

Lastly, to investigate the dynamics of deforestation permitting, we present estimates from an event study version of Equation 6:

$$\text{Log } P_{dt} = \sum_{\tau \in \mathcal{T}^{pre}} \nu_\tau ForestPop_d \cdot \gamma_t + \sum_{\tau \in \mathcal{T}^{post}} \nu_\tau ForestPop_d \cdot \gamma_t \qquad (8)$$

$$+ \mathbf{X}'_{dt}\Omega + \alpha_d + \gamma_t + \epsilon_{dt}$$

where all terms are the same as before and $\tau \in \mathcal{T}^{post}$ denotes the set of years after the FRA was implemented. The coefficients of interest are ν_τ, where $\nu_{\tau=2006}$ is omitted so that estimates are relative to the announcement year. This choice of omitted group enables us to test for anticipation effects prior to the 2008 implementation year. When $\tau \in \mathcal{T}^{post}$, the ν_τ's identify the policy impact in year τ. If districts differentially exposed to the FRA are on similar trends prior to the policy, then $\nu_\tau = 0$ when $\tau \in \mathcal{T}^{pre}$.

The key identifying assumption is that districts more and less exposed to the FRA would have remained on similar trends after 2008 had the legislation never passed. The main potential threat to identification is that less tribal districts (low treatment exposure)

[12] This exercise yields the following size groupings. Large projects: defence, mining; medium projects: irrigation, electricity, other; small projects: transportation, services, underground.

are wealthier and would have disproportionately experienced development booms in the absence of the FRA. We address this by expanding the vector $\mathbf{X}'_{dt}$ to include the set of interactions between overall tribal population, $TribalPop_d$, and time fixed effects, γ_t, in the pre- and post-period. This ensures that comparisons are made between similarly tribal districts in each period τ, exploiting differences in forest-dependency for identification.

5.2 Estimation Framework: Firm behavior

5.2.1 Main Estimating Equation

We next move from the district to the firm level in order to estimate changes in firm behavior. We estimate the average effect of the policy on firms' outcomes using a difference-in-difference equation that compares firms' land valuation in districts with greater policy exposure, before and after the policy introduction:

$$\begin{aligned} \text{Log } Y_{idt} = \beta \cdot (ForestPop_d \cdot \mathbb{1}_{t>2007}) + \psi \cdot (TribalPop_d \cdot \mathbb{1}_{t>2007}) \\ + \mathbf{X}'_{dt}\Omega + \alpha_i + \gamma_t + \epsilon_{idt} \end{aligned} \tag{9}$$

where i, d, and t index the firm, district, and year, respectively. The main outcomes are firms' land valuation and new land acquisitions. We also estimate versions where the outcome is the land revaluation rate, non-land factors of production, and TFP (Section 4.2). Left-hand side terms are as previously defined in Equation 6. α_i are firm fixed effects, which control for time-invariant differences across firms. γ_t are year fixed effects and account for boom-and-bust cycles affecting all firms.

The coefficient of interest is β, and $\beta < 0$ implies that the policy, on average, reduces firms' land valuation. Echoing the district-level specification (Equation 6), β is estimated via OLS in a TWFE setup with continuous treatment (Callaway et al., 2024), and can be interpreted as the average slope of the dose-response curve across firms. Callaway et al. (2024) formalize three assumptions to recover causal treatment effects from a difference-in-difference design with continuous treatment: (i) treatment must be continuous, which is the case since $ForestPop_d$ is a share between 0 and 1; (ii) units must not anticipate treatment, an assumption supported below with an event study; (iii) strong parallel trends: the marginal change in firm activity among firms in a district with a given tribal forest population share is the change that all firms would experience if they were surrounded by the same tribal forest population. In the absence of a formal test for this assumption, we rule out parallel trends with the dynamic equation described next.

5.2.2 Dynamic Equation

To investigate the dynamic relationship between FRA exposure and firm activity, as well as explore pre-existing trends in firm activity near tribal forestland, we present results from a dynamic version of the main equation:

$$\text{Log } Y_{idt} = \sum_{\tau \in \mathcal{T}^{pre}} \beta_\tau ForestPop_d \cdot \gamma_t + \sum_{\tau \in \mathcal{T}^{post}} \beta_\tau ForestPop_d \cdot \gamma_t + \mathbf{X}'_{dt}\Omega + \alpha_i + \gamma_t + \epsilon_{idt} \tag{10}$$

where all terms are the same as in Equation 9. The vector $\mathbf{X}'_{dt}$ includes the set of interactions between overall tribal population, $TribalPop_d$, and time fixed effects, γ_t, in the pre- and post-period. The coefficients of interest are β_τ, where $\beta_{\tau=2006}$ is omitted so that coefficients are measured relative to the annoucement year. If firm activity in treatment and control districts were on similar trends prior to the FRA, then β_τ should be statistically indistinguishable from zero when $\tau \in \mathcal{T}^{pre}$. When $\tau \in \mathcal{T}^{post}$, β_τ's identify the effect of the FRA on firms in year τ. As shown in Section 6.2, we find evidence of parallel trends and a sharp decline in land use immediately following the policy year.

5.2.3 Triple Differences

Result 3 from the model states that the policy impact on firms' land acquisition depends on initial land endowments. The intuition is that the policy involves fixed transaction costs, which matter more for smaller firms. Larger firms on the other hand benefit more from the reduced land price, since they are more likely to have larger land requirements. We test this empirically by comparing firm outcomes in treated and control districts before and after the FRA across large and small firms:

$$\text{Log } Y_{idt} = \zeta \cdot (ForestPop_d \cdot \mathbb{1}_{t>2007}) + \phi \cdot (ForestPop_d \cdot \mathbb{1}_{t>2007} \cdot Large_i) + \mathbf{X}'_{dt}\Omega + \alpha_i + \gamma_t + \epsilon_{idt} \tag{11}$$

where subscripts are defined as before. The explanatory variable of interest is the triple interaction between (i) the treatment, $ForestPop_d$, (ii) the pre-post dummy, $\mathbb{1}_{t>2007}$, which equals one in all years after 2007, and (iii) an indicator for firms with large land endowments, $Large_i$. A firm is large if its landholding is above-median in the first year that it appears in the sample. The covariate vector $\mathbf{X}'_{dt}$ includes all two-way interactions.

In this triple differences setup, ζ is the FRA impact on small firms *relative to control firms*. The coefficient of interest is ϕ, the additional impact on large firms *relative to small*

Table 1: Impact of FRA on Demand for Forestland

	(1) Log Permits	(2) IHS Permits	(3) Log Permits	(4) Log Permits
$\text{ForestPop}_d \times \mathbb{1}_{t>2007}$	-0.189***	-0.228**	-0.192***	-0.201***
	(0.072)	(0.092)	(0.046)	(0.054)
$\text{ForestPop}_d \times \mathbb{1}_{t>2007} \times \text{Medium}_i$				0.028
				(0.045)
$\text{ForestPop}_d \times \mathbb{1}_{t>2007} \times \text{Large}_i$			0.222***	0.232***
			(0.043)	(0.050)
$\text{TribalPop}_d \times \mathbb{1}_{t>2007}$	Yes	Yes	Yes	Yes
Unit of Analysis	Dist-Yr	Dist-Yr	Dist-Yr-Size	Dist-Yr-Size
District FEs	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓
Size FEs			✓	✓
Observations	11096	11096	44384	44384
R^2	0.658	0.652	0.512	0.517

Note: * $p < .1$, ** $p < .05$, *** $p <.01$. The outcome in columns 1, 3 and 4 is log(x+1), where x is the number of deforestation permits filed by developers in district d in year t. Columns 1 and 2 present difference-in-difference estimates from Equation 6. Column 2 uses the IHS transformation instead of the logarithm. Columns 3 and 4 present triple difference estimates from Equation 7. $ForestPop_d$ is tribal forest population share in district d. $TribalPop_d$ is total tribal population share. $\mathbb{1}_{t>2007}$ is a time dummy that switches on after 2007. "Large" and "Medium" are indicators for project size. All regressions control for the uninteracted components of the respective interacted variables. Standard errors clustered by district.

treated firms. An estimate of $\zeta < 0$ and $\phi > 0$ implies that smaller sized treated firms contract their operations whereas larger firms expand, in line with Result 3 of the model. Decomposing policy impacts by firm size therefore yields a crucial policy insight when viewed beside the main difference-in-difference equation: even if $\beta < 0$ in Equation 9, i.e., average firm activity declines near tribal areas, an estimate of $\zeta < 0$ and $\phi > 0$ from Equation 11 implies a changing *composition* of economic activity toward larger firms.

6 Main Results

This section presents evidence on the impact of tribal forest rights on firm behavior. We uncover an important tradeoff of conservation policy: while tribal land protections successfully reduce *average* firm activity near tribal land, the average masks a changing *composition* of economic activity toward larger firms.

6.1 Demand for Forestland

Table 1 documents how firms' demand for forestland responds to the FRA. Column 1 presents difference-in-difference estimates of Equation 6 using district-year data. The outcome is log number of deforestation permits plus one, to account for the fact that some districts may have zero developers applying for a permit in a given year. The outcome in column 2 applies the inverse hyperbolic sine transformation instead, since it is defined at zero. The key result is $\nu < 0$ in both cases: average demand for forestland by developers sharply falls after the FRA, consistent with Result 1 of the model. Quantitatively, after the FRA is enacted, firms in districts with a 1 percentage point (pp.) higher tribal forest-dependent population share file 0.19-0.23% fewer deforestation permits.

Columns 3 and 4 report triple difference estimates of Equation 7 using the district-year-size panel. We find that the downward shift in land demand is driven by small projects. To see this, column 3 pools small and medium projects (row 1) and compares them to large projects. The policy impact is negative for the non-large group, whereas the the negative effect is erased among large projects. Column 4 estimates the saturated specification and yields a similar pattern: both triple interactions are positive and increasing in size, with $\phi_{large} > \phi_{med} > 0$. This monotonically increasing size gradient aligns with with the model's mechanism: policy-induced transaction costs reduce land demand on average, but the corresponding decline in land prices shifts permitting toward larger projects that can better absorb policy costs. We provide direct evidence of this mechanism in Section 6.2 using firm-level data on land purchases and prices.

Appendix Figure B3 presents alternative size-based demand estimates. Coefficients are from estimating three versions of Equation 6 where the outcome is log number of permits for small, medium, and large projects. The plotted difference-in-difference coefficients map directly to the triple-difference coefficients in Equation 7. The small-project estimate maps to ν, while the medium and large estimates map to $\nu + \phi_{\text{med}}$ and $\nu + \phi_{\text{large}}$, respectively. Once again, demand for forestland falls sharply for developers of small projects, declines less for medium projects, and is near-zero for large projects.[13]

Figure 4 plots dynamic estimates of Equation 8 for all projects (dark) and large projects (light), normalized to 2006 to capture behavior around the policy announcement and implementation years. Besides 2003, all pre-policy coefficients are statistically indistinguishable from zero. After policy implementation in 2008, coefficients turn weakly negative

[13]Figure B4 presents estimates from separate regressions by project category, ordered from left to right in decreasing order of mean project size. There is little heterogeneity across categories. While one may have expected smaller effects for larger projects like mines, note that each estimate is at the district level and pools over heterogeneous firms within a category (e.g., small vs large mines). Heterogeneity by size category (Tabe 1) or by individual firm size, which we present in Section 6.2.3 with firm-level data, is therefore more informative for testing Result 3 from the theory.

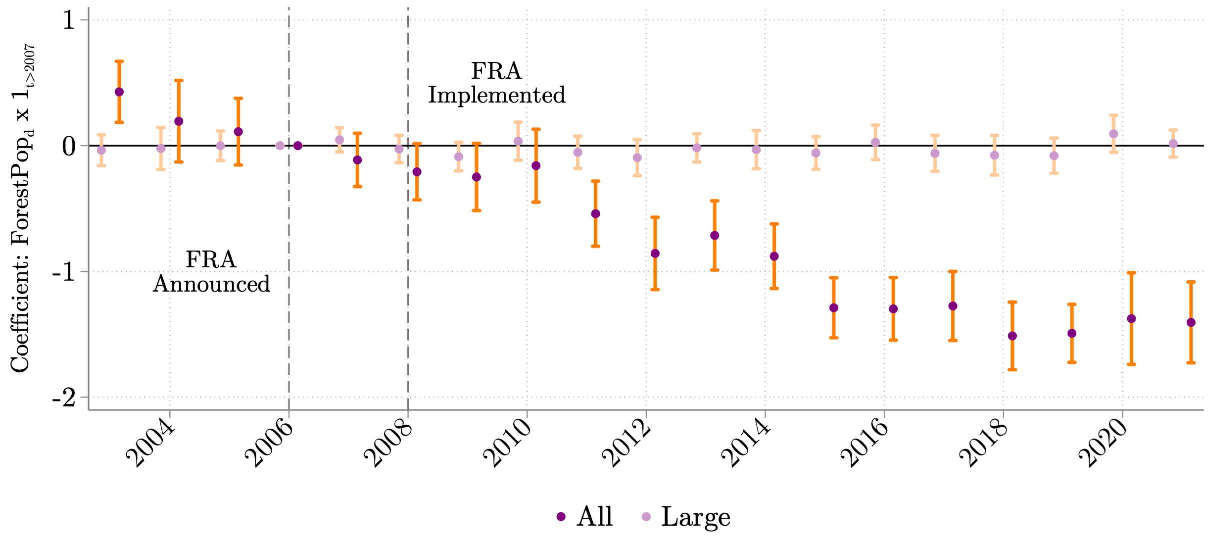

Figure 4: Event Study—Demand for Forestland

Note: * $p < .1$, ** $p < .05$, *** $p < .01$. The unit of observation is a district-year. Dark and light dots are coefficients from Equation 8 where the outcome is log number of permits filed for all projects (plus one), and for large projects, respectively. Bars are 95% confidence intervals. All specifications include district and year fixed effects as well as controls for temperature and rainfall. Standard errors clustered by district.

($p < 0.1$), and then become sharply negative ($p < 0.01$) after 2010. This sharp drop coincides with a late-2009 policy amendment that enforced the Gram Sabha consent requirement (Section 2).[14] The persistent decline in land demand is strikingly absent for large projects, which display flat pre-trends and near-zero coefficients throughout the event study window. Figure 4 thus confirms that the post-policy decline in land demand is concentrated among smaller projects, consistent with the triple difference results.[15]

Having established that the FRA reduces demand for forestland, with weaker effects for large projects, we proceed to validate these findings with satellite data. Appendix C.3 uses satellite deforestation measures to test whether the FRA leads to: (i) less forest loss near tribal areas, and (ii) muted effects in heavily industrial districts. Reassuringly, the average-versus-compositional distinction emerges in satellite imagery (Table A9). While deforestation declines on average, we document intensifying forest loss in districts with larger projects. This robustness exercise strengthens internal validity by showing that our findings from administrative data are echoed in independent satellite imagery.

Next, we move down to the firm level to understand how individual firms contribute

[14] Official policy can be read here: `https://forestrightsact.com/wp-content/uploads/2016/04/moef_circular_on_diversion_fra.pdf`.

[15] One plausible explanation for the 2003 spike is a mining boom in tribal areas. However, this would have generated a persistent pre-trend, not a single year deviation. Moreover, large projects (which include mining) would have displayed a positive pre-trend, which is not the case.

Table 2: Impact of FRA on Firm Land Use

	(1) Land Value	(2) Land Purchase (=1)	(3) Revaluation Rate
ForestPop$_d$ x $\mathbb{1}_{t>2007}$	-0.333***	0.032**	-0.014***
	(0.061)	(0.016)	(0.005)
TribalPop$_d$ x $\mathbb{1}_{t>2007}$	Yes	Yes	Yes
Firm FEs	✓	✓	✓
Sector FEs	✓	✓	✓
Year FEs	✓	✓	✓
Observations	313465	313465	313465
R^2	0.868	0.396	0.245

Note: The unit of observation is a firm-year. Column 1 is log of closing book value of land. Column 2 is an indicator of whether land was purchased during the accounting year. Column 3 is log of the revaluation rate, measured as the revaluation of the opening land stock divided by the opening value. $ForestPop_d$ is tribal forest population share in district d. $TribalPop_d$ is total tribal population share. $\mathbb{1}_{t>2007}$ is a time dummy that switches on after 2007. All regressions control for the uninteracted components of the respective interacted variables. Standard errors clustered by firm.

to the aggregate decline in land demand and the implications for firm composition.

6.2 Firm behavior

6.2.1 Main Estimates

Firm level estimates of Equation 9 are presented in Table 2. The outcome in column 1 is log value of firms' landholdings. We find $\beta < 0$: the policy successfully reduced firm activity near tribal forestland. This corroborates Result 1 from the model, which states that the policy reduces land demand by firms. The point estimate implies that firms in districts with 1 pp. higher tribal forest-dependent populations have 0.3 pp. lower land valuations after the FRA compared to firms in districts with less policy exposure.

Columns 2 and 3 show estimates of treatment effect for the probability of land expansion (denoted by $\Delta\psi(l)$ in the model) and log land revaluation rate ($\frac{p^{**}}{p^{*}}$), respectively. These estimates reveal the extent to which the decline in land valuations is driven by changes in land acquisition versus changes in price. The positive coefficient in column 2 implies that the FRA on average increased the probability of land acquisition by firms. Our model predicts that the FRA's effect on the probability of land acquisition is ambiguous and depends on the firm's initial landholding. As we show in Table 3 below, the effect is indeed heterogeneous across firm size. Since the land valuation falls on average, in spite of land acquisition likelihood increasing, the valuation change must come via land price falling. Column 3 confirms this argument: the land revaluation rate declines

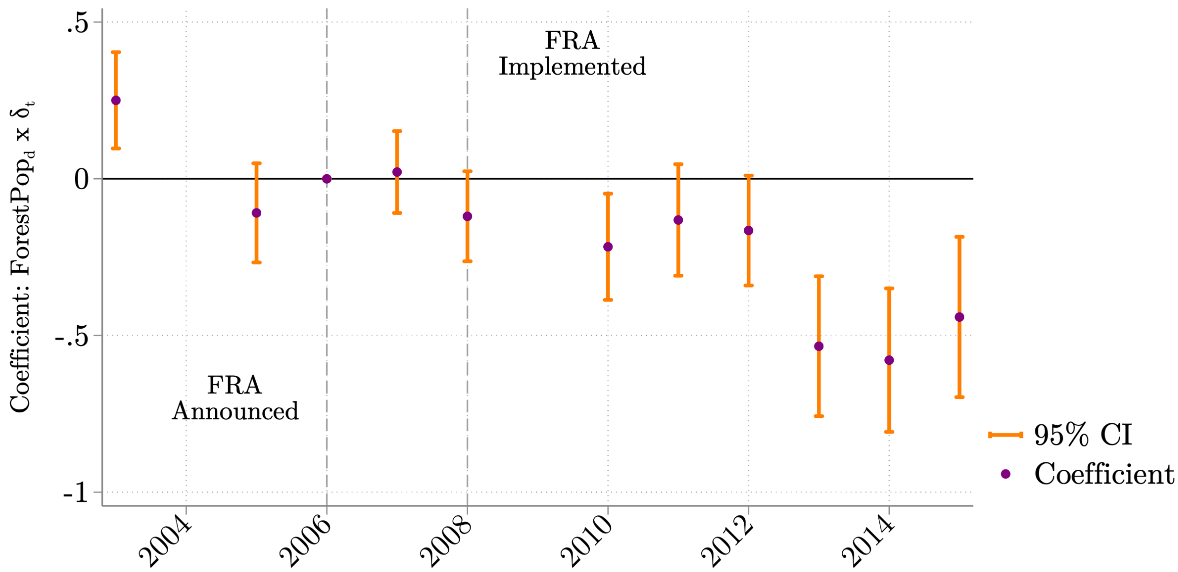

Figure 5: Event Study—Firm Level Estimates

Note: Purple circles are coefficients from Equation 10. The outcome is log land value. x-axis is number of years since 2008, when the FRA was enacted. The omitted year is 2007. Bars are 95% confidence intervals.

after the FRA, consistent with land price falling from p^* to p^{**} in the model.

Dynamic estimates of Equation 10 using land valuation as the outcome are plotted in Figure 5. Coefficients fluctuate around zero prior to policy implementation and then turn sharply and persistently negative after 2008. Relatively stable pre-trends and sharp negative effects following the policy year provide reassurance that we capture impacts of tribal forest rights rather than differential trends between tribal and non-tribal districts.

6.2.2 Robustness of Main Estimates

Table A4 presents a variety of robustness tests of our preferred specification with land value as the outcome. Starting with robustness to sample restrictions, recall that our preferred estimation sample excludes 2004 and 2009 due to disproportionately fewer firm matches during the data harmonization process for these years. Column 1 shows that the estimates are virtually identical when these years are added back to the sample, suggesting that our preferred estimates are not biased by dropping these years.

Columns 2 and 3 test alternative definitions of the treatment variable, $ForestPop_d$. Instead of tribal population share within 1km of the forest, column 2 measures policy exposure as the districts' tribal population share living in villages within the first quartile of distance to the forest edge. Column 3 uses a below-median threshold. The coefficient is robust in both cases, suggesting that our results do not hinge on the chosen proximity cutoff and instead reflect a broader relationship between policy exposure and the outcome.

Columns 4-6 tests robustness to alternative fixed effects. Column 4 adds sector-by-year fixed effects to account for time-varying unobserved heterogeneity across sectors (2-digit NIC codes), such as differences in sector-specific business cycles. The coefficient is virtually unchanged from the baseline estimate. Column 5 includes firm age fixed effects, where age is the difference between year t and the firm's year of creation. This ensures β is identified from comparing firms at the same life-cycle stage, which is important in case the FRA differentially affects younger and older firms. The coefficient remains stable. Column 6 shows a nearly equivalent coefficient when controlling for exit year fixed effects, defined as the final year that a firm appears in the sample. This accounts for selective firm exit, which may bias our main estimate if exiting firms feature unobserved characteristics correlated with land use. Once again, the coefficient remains robust.

Column 7 tests robustness to dropping outliers. We follow Allcott et al. (2016), who also use ASI data, and drop observations where input costs (land, labor, or capital) are more than twice the value of output. Despite having already truncated these variables at the 95th percentile, this procedure drops an additional 10,674 observations. Nevertheless, the coefficient remains stable, suggesting that our main estimates are unbiased by outliers.

Lastly, we present a test to rule out contamination bias. If the FRA causes firms to relocate to less tribal areas and evade the policy, then our control group is contaminated and β would be overestimated. This violates SUTVA, which states that β is well identified if firm activity in district d depends on policy exposure in district d only. Since our treatment variable is at the district level, spatial spillovers *within the district* are already captured by β. Contamination bias is therefore only a concern if firms move *across districts*. To rule this out, we estimate a version of Equation 9 where the outcome is an indicator for whether firm i moved districts between time t and $t-1$. This test exemplifies the value of matching firm and district identifiers in the ASI (Section 4.2), which enables us to track within-firm changes in district IDs over time. We find no evidence of contamination bias (Table A5, Column 1), suggesting that our findings are not biased by spatial spillovers.

6.2.3 Heterogeneity by Firm Size

We have thus far documented what appears to be a success story: the FRA reduces firms' *average* land use near tribal forestland. However, our key theoretical result is that this *average* change masks a *compositional* shift of economic activity towards larger industry. Next, we present estimates of treatment heterogeneity by firm size to test this theory.

Triple difference estimates of Equation 11 are reported in Table 3. The interaction coefficient (row 2) captures heterogeneous responses of large firms for the same outcomes as above. The key takeaway is that large firms are more resilient to the FRA compared to

Table 3: Triple Difference Estimates: Heterogeneity by Firm Size

	(1) Land Value	(2) Land Purchase (=1)	(3) Revaluation Rate
ForestPop$_d$ x $\mathbb{1}_{t>2007}$	-0.621***	-0.034**	-0.010***
	(0.065)	(0.013)	(0.004)
ForestPop$_d$ x $\mathbb{1}_{t>2007}$ x Large$_i$	0.384***	0.101***	-0.008
	(0.109)	(0.027)	(0.010)
TribalPop$_d$ x $\mathbb{1}_{t>2007}$	Yes	Yes	Yes
Firm FEs	✓	✓	✓
Sector FEs	✓	✓	✓
Year FEs	✓	✓	✓
Observations	313465	313465	313465
p-value (equality)	0.000	0.000	0.882
R^2	0.869	0.398	0.245

Note: The unit of observation is a firm-year. Column 1 is log of closing book value of land. Column 2 is an indicator of whether land was purchased during the accounting year. Column 3 is log of the revaluation rate, measured as the revaluation of the opening land stock divided by the opening value. $ForestPop_d$ is tribal forest population share in district d. $TribalPop_d$ is total tribal population share. $\mathbb{1}_{t>2007}$ is a time dummy that switches on after 2007. $Large_i$ is an indicator for whether firm land value is above median at baseline. All regressions control for the uninteracted components of the respective interacted variables. Standard errors clustered by firm.

small firms. The interaction coefficient in column 1 is positive and significant, implying that the land value of large firms increases after the policy, although not enough to fully offset the decline in value among small firms. Column 2 shows that the increase in land value among large firms comes from increases in land purchases ($\Delta\psi(l)$). In contrast, the decline in land value for small firms comes from lower land demand (column 2, row 1). Both of these findings lend empirical support to Result 3 from the model. Column 3 compares the revaluation rate ($\frac{p^{**}}{p^*}$) across large and small firms. We find no evidence of heterogeneity, in line with Result 5 from the model. The intuition is that revaluation is homogeneous across all firms in a market, regardless of size, since they all face the same land price. Overall, our estimates of treatment heterogeneity indicate a pattern of land expansion among larger firms and contraction among smaller firms.

Table A6 tests sensitivity of our triple difference estimates to the same robustness checks as the preferred difference-in-difference specification (Section 6.2.2). In particular, we consider alternative treatment definitions, sector-by-year and firm age fixed effects, exit year fixed effects, and dropping outliers. The main and interaction coefficient are highly stable and remain statistically significant across all robustness tests.

6.2.4 Downstream Effects: Production Function Estimates

As an extension, we estimate the impact of the FRA on second order parameters from the model, including capital, labour, output ($Q(l)$), and TFP ($\tilde{z}$). This serves two purposes: first, it enables us to validate model predictions about policy-induced changes in average firm productivity. Second, it probes model robustness more generally since capital and labour are complementary to land. Although we abstracted from these inputs in the model, we expect downward adjustment along both margins as firms' land use declines.

Table A7 presents estimates of Equation 9 where the outcomes are the log of closing capital stock (column 1), employees (column 2), output (column 3), and TFP (column 4). We find sharp declines in capital and labour, echoing our findings for land, and suggesting that inputs are complements. Output also declines, although estimate precision is low. Lastly, the FRA reduces TFP by 1.24% in districts with 10 pp. higher treatment intensity. This finding is important because the effect is theoretically ambiguous (Result 6). For small firms, the cost of FRA-mandated informed consent raises the productivity threshold for expansion. This reduces the probability of investing in new projects, but raises the productivity of new projects *conditional* on investing. The first effect always dominates, reducing the expected productivity of small firms. For large firms, the FRA lowers the productivity threshold, increasing the probability of new projects as well as average productivity. The negative sign on our TFP estimate implies that the contractionary force among small firms dominates in equilibrium.

Table A8 presents estimates of treatment heterogeneity by firm size for capital, labour, output, and TFP. Since small firms contract landholdings and larger firms expand, we expect the same directionality for these other parameters due to complementarities. Indeed, column 1 documents a large decline in capital valuation for small firms and a smaller impact for larger firms, even though the effect on them is also negative. We also observe opposing coefficient signs for labour and output, but statistical precision is weak. One possible explanation is the sequence of firm expansion: land and capital investments often precede labour hiring and revenue realization, dampening contemporaneous estimates of these downstream outcomes. Lastly, the policy impact on TFP draws in opposite directions for small and large firms. Both coefficients are statistically significant, thus corroborating Result 6 of the model.

7 Land Conflict, Population Displacement, and Welfare

The change in the level and composition of firm activity due to the FRA has ambiguous welfare effects on local tribal populations. On one hand, the post-policy decline in firm

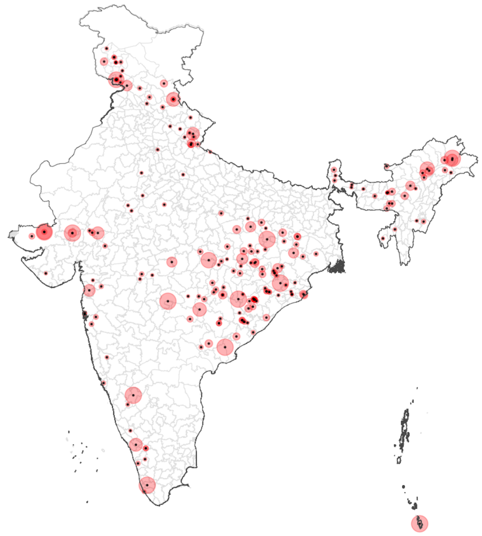

Figure 6: Land Conflicts

Note: Data are from Land Conflict Watch for 2001-2020. Black dots denote the location of land conflicts. Red circles describe the land area under dispute.

activity, and the associated reduction in pressure on forestland (Table 1, Table A9), potentially raises tribal welfare. On the other hand, the post-policy shift in the composition of firm activity toward larger firms, which typically impose more ecological damage, may reduce tribal welfare. The net welfare effect thus depends on whether the adverse impacts of large-firm expansion outweighs the aggregate fall in forest encroachment.

7.1 Measuring Land Conflict

Measuring the impact of the FRA on tribal welfare is inherently challenging. Their valuation of forests extends beyond immediate consumption or income needs and is also associated with their ability to maintain forest-based livelihoods. To document otherwise unobserved welfare impacts of the FRA, we assemble novel data on land conflicts and population displacement obtained through a data agreement with Land Conflict Watch (LCW), a private agency that tracks land conflicts reported in the media.[16] LCW defines land conflicts as any formal or informal contestation over land ownership, control, use, or involving a local community and carrying public interest. The presence of a land conflict, therefore, signals the dissatisfaction of the local community with the land use or access

[16] All records are verified by LCW through administrative and legal records and field visits by their staff.

of some private or public entity. We obtained land conflict coordinates, start year, sector, contested area, and number of people displaced for 138 conflicts between 2001-2020.

Although LCW do not indicate whether affected communities are tribal, a visual comparison of conflict locations (Figure 6) and treatment intensity (Figure 3) shows clear overlap. Land conflicts cluster around India's tribal belt, the Northeast, and the Northern Himalayas—the same regions where treatment intensity is highest. Table A10 formalizes this pattern with a cross-sectional regression of cumulative conflicts on treatment intensity ($ForestPop_d$), controlling for overall tribal population share and state fixed-effects. The correlation is strong, positive, and robust to alternative transformations of the conflict measure, suggesting that land conflicts concentrate where tribal populations depend on forests. It is thus likely that many land conflicts in our data involve tribes, enabling us to interpret FRA-induced changes in land conflict as informative about tribal welfare.

7.2 Estimation and Results

To formally estimate the impact of the FRA on land conflicts and population displacement, we first aggregate conflicts into a balanced district–year panel, treating districts with no recorded incidents as having experienced zero land conflicts. We then estimate a difference-in-difference equation as follows:

$$\begin{aligned} \text{Log}\left(C_{dst}+1\right) = \vartheta \cdot \left(ForestPop_d \cdot \mathbb{1}_{t>2007}\right) + \xi \cdot \left(TribalPop_d \cdot \mathbb{1}_{t>2007}\right) \\ + \mathbf{X}'_{dt}\Omega + \alpha_s + \gamma_t + \epsilon_{dst} \end{aligned} \tag{12}$$

where d, s, and t index the district, state, and year, respectively. The outcome, C_{dst}, measures cumulative number of land conflicts with developers, or the cumulative number of local community members displaced as a result. Remaining explanatory variables are defined as before (Equation 6). We estimate this equation on the subsample of districts that experienced at least one conflict during the study period. We also estimate it separately for conflicts over small and large land parcels, measured by below- and above-median parcel size. Lastly, we include state fixed effects, γ_s, instead of district fixed effects because there is insufficient identifying variation over time within districts. The coefficient of interest is ϑ. Conditional on a district experiencing any conflict, ϑ captures the percent change in conflicts after the FRA is enacted in districts with greater treatment intensity.

Columns 1-4 of Table 4 reports estimates of Equation 12 for land conflict. Total land conflict rises after the FRA is enacted (column 1), driven mainly by disputes over large projects (column 3). Column 1 estimate implies that a 10 percentage point increase in forest dependent tribal population in a district post-FRA, increases number of land con-

Table 4: Impact of FRA on Land Conflicts

	Log Land Conflict				Log Population Displacement			
	(1) Total	(2) Small	(3) Large	(4) Intensity	(5) Total	(6) Small	(7) Large	(8) Intensity
$\text{ForestPop}_d \times \mathbb{1}_{t>2007}$	0.379**	0.157	0.323*	0.765*	3.971*	0.263	4.434**	0.988*
	(0.155)	(0.195)	(0.173)	(0.451)	(2.263)	(0.860)	(2.209)	(0.557)
$\text{TribalPop}_d \times \mathbb{1}_{t>2007}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FEs	✓	✓	✓	✓	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓	✓	✓	✓	✓
Observations	2040	2040	2040	2040	2040	2040	2040	2040
R^2	0.481	0.301	0.264	0.389	0.278	0.285	0.215	0.276

Note: Data are at the district-year level. All outcomes are measured as log(x+1). The outcomes in columns 1-3 are cumulative number of land conflicts overall, and associated with small and large development projects, respectively. Column 4 is cumulative project area under conflict divided by cumulative number of conflicts. The outcome in columns 5-7 are cumulative number of people displaced through land contestation overall and by small and large developers, respectively. Column 8 is cumulative people displaced divided by cumulative number of conflicts. All regressions control for the uninteracted components of the respective interacted variables. Standard errors clustered by district.

flicts by about 3.8%. The same pattern emerges in mean land area per conflict (column 4), where the positive and significant point estimate indicates that post-FRA conflicts involve larger land parcels. Columns 5-8 use population displacement from these land conflicts as the outcome, a measure more closely tied to tribal welfare. Total displacement rises post-policy (column 5), again due to conflict over large projects (column 7). Displacement per conflict also rises post-policy (column 8), consistent with post-FRA land conflicts centering around larger, potentially more disruptive, development projects. The point estimate implies that displacement per conflict is roughly 10% higher in districts with a 10 pp. higher forest-dependent tribal population share after the FRA is passed. This clearly signals a negative impact on tribal welfare, a topic which we elaborate next.

7.3 Implications for Tribal Welfare

From a welfare perspective, our findings in Table 4 suggest that welfare losses associated with large-scale forest diversion more than offset any welfare gains from reduced average firm activity. This can be seen in light of the paper's key result: the FRA lowers the *level* of firm activity near tribal areas (Table 2), but shifts the *composition* toward larger firms that continue to divert forests for expansion (Table 6). As a result, even as average firm activity declines, remaining projects are more land-intensive and displace more people, leading to higher conflict intensity and negative pressure on welfare.

We wish to clarify that the rise in conflict over large projects need not only reflect direct confrontation between developers and tribes. It may also reflect increased tribal empowerment under the FRA. Even if the number of deforestation permits filed by large projects does not increase in absolute terms (Figure B3), affected tribes may be more able and willing to escalate disputes after having their land rights formally recognized[17]. This explains the positive coefficient across all columns in Table 4. However, if this was the only reason for increased conflict and displacement, then there would be similar coefficient sizes across small and large projects, since the FRA uniformly empowers local communities *conditional* on project size. Instead, we find that post-FRA conflict and displacement increases more for large projects. While the difference between columns 2 and 3 is positive but imprecise, the difference between columns 6 and 7 is statistically significant. This is consistent with our result that the FRA increases the probability of expansion for large firms (Table 3). Hence, some of the post-FRA rise in conflict and population displacement is due to greater activity of large firms.

Regardless of whether the mechanism is through more effective resistance or changing composition of firm activity, the equilibrium outcome is the same: development-driven land conflict and population displacement increase after the FRA. These patterns point to higher social disruption and, consequently, welfare losses in affected tribal areas.

8 Conclusion

This paper asks whether formalizing tribal land rights can protect indigenous land from industrial encroachment. Answering this question is urgent and policy-relevant as global manufacturing growth intensifies land competition between developers and tribes. Using India's landmark Forest Rights Act—the world's first nationwide tribal land titling reform—as a natural experiment, we document reduced firm activity near tribal areas on *average*, but a shift in the *composition* of economic activity toward larger firms.

Our model of firm behavior provides an explanation for these findings: land rights raise land acquisition costs, resulting in falling land prices. These higher costs disproportionately burden smaller firms, while large firms benefit more from low prices and expand into marginal projects. We document this average-versus-compositional distinction using deforestation permits, a firm-level panel of production activity, and satellite

[17]The findings of this section are best reflected with anedotal evidence. The Vedanta mining company proposed a bauxite mine in Odisha's Niyamgiri Hills in 2003, home to the Dongaria Kondh and Kutia Kondh tribes. Project authorities received a deforestation permit in 2004, and construction began in 2009, after the FRA was passed. At the same time, the FRA also strengthened tribal communities' ability to contest diversion. Protests by local tribes intensified in 2009, followed by an expert report citing FRA violations that informed consent was ignored. The Supreme Court of India subsequently required Gram Sabha consent, and the project was banned in 2014.

imagery. Consistent evidence across three data sources strengthens internal validity.

Our analysis is not without limitations. First, we cannot measure treatment using issued titles due to data unavailability. However, our proxy measure is better because titling is endogenous to local governance capacity. Second, our firm panel only covers manufacturing firms, precluding analyses of how other sectors respond to rights recognition. Lastly, we lack data on tribal livelihoods, preventing direct measurement of welfare impacts. Even so, by leveraging geocoded data on land conflicts, we are able show that the policy heightens land conflicts, a social margin tightly linked to welfare.

Our findings have clear policy relevance for India. They suggest that formal recognition of tribal rights need not hamper economic development; instead, it creates a trade-off between reduced average firm activity and the survival of larger industry. This re-sorting of development pressure implies that enforcement and monitoring should focus on heavy industry (e.g., mining and defence), and that land rights reforms should be complemented by compensation schemes tied to project scale, such as revenue sharing or co-ownership. Lastly, higher incidence of land conflicts underscores the need for complementing rights recognition with credible and accessible dispute resolution institutions that reduce the scope for contested development.

We believe that our findings are also externally valid, as governments around the world consider formalizing indigenous land rights as part of broader climate, conservation, and environmental justice agendas. For example, Canada is implementing the United Nations Declaration on the Rights of Indigenous Peoples through federal legislation, which commits the state to decision-making processes with Indigenous peoples' free, prior, and informed consent (Department of Justice Canada, 2025). In the developing world, Colombia recently operationalized Indigenous Territorial Entities through Decree 488, strengthening tribal authority over land in the Amazon (República de Colombia, 2025; Associated Press, 2025). These cases reflect a global shift toward strengthening indigenous land tenure. Our results suggest that such reforms can protect tribal land from industrial encroachment, but that surviving large firms may trigger land conflict, making complementary institutions central to whether rights recognition delivers welfare gains.

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A Appendix Tables

Table A1: Project Summary Statistics

	Num. Projects	Mean Size (ha.)	SD (ha.)	Total Area (ha.)
Defense	621	207.3	1,954.9	128,761.7
Mining	2,074	202.5	1,728.8	420,023.6
Other	6,431	28.7	553.8	184,288.0
Irrigation	2,853	27.6	128.0	78,817.7
Electricity	5,079	23.7	211.5	120,625.5
Transportation	16,806	9.0	143.4	151,067.4
Services	4,044	2.2	38.1	9,049.3
Underground	4,127	1.4	3.5	5,755.2
Total	42,035	26.1	517.5	1,098,388.5

Note: Sample consists of all project proposals submitted between 2003-2021. Total Area is the total area earmarked for deforestation over the study period.

Table A2: ASI Summary Statistics

	Observations	Mean	SD
Land	403369	30.95	72.74
Land Purchase	403369	0.31	1.17
Purchased Land (=1)	403369	0.08	0.27
Capital	403369	593.17	1275.18
Labor	401779	123.27	176.91
Output	340536	2295.91	4240.51

Note: Values are in constant 2005 USD Thousand dollars. Land is closing book value of land. Land Purchase is the value of new land purchased during the accounting year. Labor is total number of employees.

Table A3: Correlation between Tribal Population and Tribal Forest Population

	(1) ForestPop_d	(2) ForestPop_d
TribalPop_d	0.713***	0.551***
	(0.038)	(0.053)
Outcome Mean	0.093	0.092
State FEs		✓
Observations	584	580
R^2	0.763	0.855

Note: Data are at the district level. The outcome is tribal population share living within 1km of the forest. The explanatory variable is the overall tribal population share. Standard errors robust to heterogeneity.

Table A4: Robustness Checks: Main Difference-in-Difference Estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ForestPop$_d$ x $\mathbb{1}_{t>2007}$	-0.343***	-0.310***	-0.162***	-0.314***	-0.342***	-0.333***	-0.335***
	(0.058)	(0.060)	(0.051)	(0.062)	(0.062)	(0.061)	(0.061)
TribalPop$_d$ x $\mathbb{1}_{t>2007}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Full	Preferred	Preferred	Preferred	Preferred	Preferred	Preferred
Treatment Distance	1km	Q1	Q2	1km	1km	1km	1km
Firm FEs	✓	✓	✓	✓	✓	✓	✓
Sector FEs	✓	✓	✓		✓	✓	✓
Year FEs	✓	✓	✓		✓	✓	✓
Sector $\times$ Year FEs				✓			
Age FEs					✓		
Exit Year FEs						✓	
Drop Outliers	No	No	No	No	No	No	Yes
Observations	341917	313465	313465	313433	307767	313465	303043
R^2	0.868	0.868	0.868	0.868	0.871	0.868	0.870

Note: Data are at the firm-year level. The outcome is log of the closing book value of land. $TribalPop_d$ is total tribal population share. $\mathbb{1}_{t>2007}$ switches on after 2007. The full sample (column 1) includes the years 2004 and 2009, whereas the preferred sample (columns 2-7) does not. In columns 2 and 3, $ForestPop_d$ is the tribal population share living within the 1st and 2nd distance quartile from the forest edge. In remaining columns it is the share living within 1km of the forest. Column 4 adds sector-year fixed effects. Columns 5 and 6 add firm age and firm exit year fixed effects. Column 7 drops outliers. All regressions control for the uninteracted components of the respective interacted variables. Standard errors clustered by firm.

Table A5: Impact of FRA Policy on Firm Mobility

	(1) Moved (=1)	(2) Moved (=1)
ForestPop$_d$ x $\mathbb{1}_{t>2007}$	0.032	0.034
	(0.021)	(0.026)
ForestPop$_d$ x $\mathbb{1}_{t>2007}$ x Large$_i$		0.017
		(0.030)
TribalPop$_d$ x $\mathbb{1}_{t>2007}$	Yes	Yes
Firm FEs	✓	✓
Sector FEs	✓	✓
Year FEs	✓	✓
Observations	217019	217019
R^2	0.360	0.360

Note: Data are at the firm-year level and outcomes are an indicator for whether the firm moved districts in the past year. $ForestPop_d$ is tribal forest population share. $TribalPop_d$ is total tribal population share. $\mathbb{1}_{t>2007}$ switches on after 2007. $Large_i$ is an indicator for whether firm land value is above median at baseline. All regressions control for the uninteracted components of the respective interacted variables. Standard errors clustered by firm.

Table A6: Robustness Checks: Heterogeneity by Firm Size

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ForestPop$_d$ x $\mathbb{1}_{t>2007}$	-0.620***	-0.605***	-0.415***	-0.590***	-0.621***	-0.621***	-0.614***
	(0.061)	(0.064)	(0.059)	(0.065)	(0.066)	(0.065)	(0.064)
ForestPop$_d$ x $\mathbb{1}_{t>2007}$ x Large$_i$	0.411***	0.404***	0.383***	0.372***	0.362***	0.384***	0.373***
	(0.107)	(0.104)	(0.067)	(0.109)	(0.111)	(0.109)	(0.110)
TribalPop$_d$ x $\mathbb{1}_{t>2007}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Full	Preferred	Preferred	Preferred	Preferred	Preferred	Preferred
Treatment Distance	1km	Q1	Q2	1km	1km	1km	1km
Firm FEs	✓	✓	✓	✓	✓	✓	✓
Sector FEs		✓	✓		✓	✓	✓
Year FEs		✓	✓		✓	✓	✓
Sector × Year FEs	✓			✓			
Age FEs					✓		
Exit Year FEs						✓	
Drop Outliers	No	No	No	No	No	No	Yes
Observations	341917	313465	313465	313433	307767	313465	303043
R^2	0.869	0.869	0.869	0.869	0.872	0.869	0.871

Note: Data are at the firm-year level. The outcome is log of the closing book value of land. $TribalPop_d$ is total tribal population share. $\mathbb{1}_{t>2007}$ switches on after 2007. $Large_i$ is an indicator for whether firm land value is above median at baseline. The full sample (column 1) includes the years 2004 and 2009, whereas the preferred sample (columns 2-7) does not. In columns 2 and 3, $ForestPop_d$ is the tribal population share living within the 1st and 2nd distance quartile from the forest edge. In remaining columns it is the share living within 1km of the forest. Column 4 adds sector-year fixed effects. Columns 5 and 6 add firm age and firm exit year fixed effects. Column 7 drops outliers. All regressions control for the uninteracted components of the respective interacted variables. Standard errors clustered by firm.

Table A7: Impact of FRA Policy on Factors of Production

	(1) Capital	(2) Labor	(3) Output	(4) TFP
ForestPop$_d$ x $\mathbb{1}_{t>2007}$	-0.456***	-0.137***	-0.036	-0.120**
	(0.063)	(0.048)	(0.072)	(0.056)
TribalPop$_d$ x $\mathbb{1}_{t>2007}$	Yes	Yes	Yes	Yes
Firm FEs	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓
Sector FEs	✓	✓	✓	✓
Observations	313468	313468	313468	313468
R^2	0.941	0.918	0.908	0.712

Note: The unit of observation is a firm-year. All outcomes are in logs. Column 1 is value of fixed capital, column 2 is number of employees, column 3 is value of output, and column 4 is TFP measured using the Levinsohn and Petrin (2003) approach. $ForestPop_d$ is tribal forest population share in district d. $TribalPop_d$ is total tribal population share. $\mathbb{1}_{t>2007}$ is a time dummy that switches on after 2007. All regressions control for the uninteracted components of the respective interacted variables. Standard errors clustered by firm.

Table A8: Heterogeneity by Firm Size: Production Function Estimates

	(1) Capital	(2) Labour	(3) Output	(4) TFP
ForestPop$_d$ x $\mathbb{1}_{t>2007}$	-0.645***	-0.131**	-0.043	-0.225***
	(0.077)	(0.057)	(0.084)	(0.064)
ForestPop$_d$ x $\mathbb{1}_{t>2007}$ x Large$_i$	0.266***	0.075	0.021	0.273***
	(0.100)	(0.081)	(0.124)	(0.094)
TribalPop$_d$ x $\mathbb{1}_{t>2007}$	Yes	Yes	Yes	Yes
Firm FEs	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓
Sector FEs	✓	✓	✓	✓
Observations	313468	313468	313468	313468
p-value (equality)	0.000	0.091	0.725	0.000
R^2	0.941	0.918	0.908	0.712

Note: The unit of observation is a firm-year. All outcomes are in logs. Column 1 fixed capital, column 2 is total number of employees, column 3 is output, and column 4 is TFP estimated with the Levinsohn and Petrin (2003) production function approach. $ForestPop_d$ is tribal forest population share in district d. $TribalPop_d$ is total tribal population share. $\mathbb{1}_{t>2007}$ is a time dummy that switches on after 2007. $Large_i$ is an indicator for whether firm land value is above median at baseline. All regressions control for the uninteracted components of the respective interacted variables. Standard errors clustered by firm.

Table A9: Impact of FRA Policy on Deforestation

	(1) Deforestation	(2) Deforestation
ForestPop$_d$ x $\mathbb{1}_{t>2007}$	-0.004*	-0.008
	(0.002)	(0.005)
ForestPop$_d$ x $\mathbb{1}_{t>2007}$ x Large$_d$		0.019***
		(0.007)
TribalPop$_d$ x $\mathbb{1}_{t>2007}$	Yes	Yes
District FEs	✓	✓
State × Year FEs	✓	✓
Observations	9860	9010
R^2	0.875	0.888

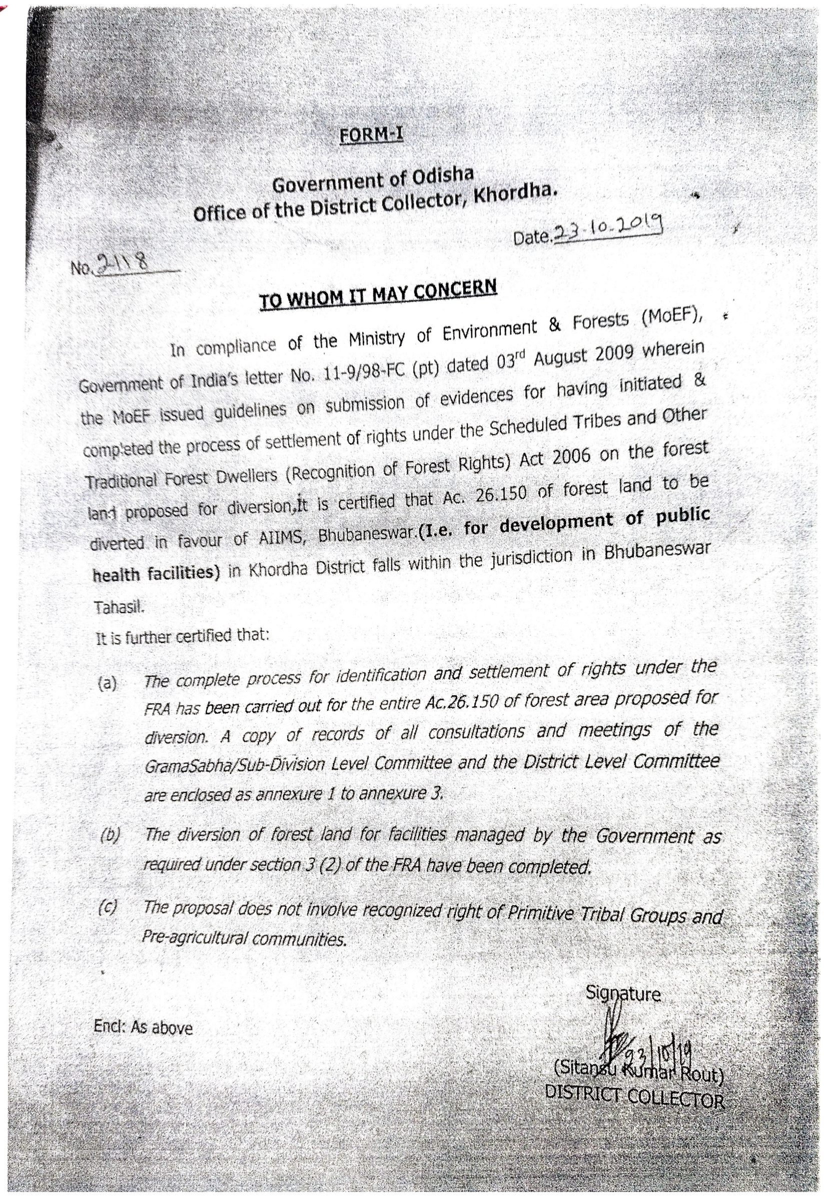
Note: Data are at the district-year level. The outcome is hectares deforested divided by district land area. $Large_d$ is the proportion of firms in district d with above-median landholdings. All regressions control for the uninteracted components of the respective interacted variables. Standard errors clustered by district.

Table A10: Cross-Sectional Correlation: Total Land Conflicts and Treatment Intensity

	(1) Conflicts	(2) Log Conflicts	(3) IHS Conflicts
ForestPop$_d$	0.850**	0.382**	0.500**
	(0.339)	(0.160)	(0.208)
TribalPop$_d$	Yes	Yes	Yes
State FEs	✓	✓	✓
Observations	580	580	580
R^2	0.277	0.287	0.287

Note: Data are at the district level. The outcome is the cumulative number of land conflicts ever recorded in a district by the end of the study period. $ForestPop_d$ is tribal forest population share in district d. $TribalPop_d$ is total tribal population share. Standard errors clustered by district.

B Appendix Figures



FORM-I

Government of Odisha
Office of the District Collector, Khordha.

No. 2118

Date. 23.10.2019

TO WHOM IT MAY CONCERN

In compliance of the Ministry of Environment & Forests (MoEF), Government of India's letter No. 11-9/98-FC (pt) dated 03rd August 2009 wherein the MoEF issued guidelines on submission of evidences for having initiated & completed the process of settlement of rights under the Scheduled Tribes and Other Traditional Forest Dwellers (Recognition of Forest Rights) Act 2006 on the forest land proposed for diversion, It is certified that Ac. 26.150 of forest land to be diverted in favour of AIIMS, Bhubaneswar. **(I.e. for development of public health facilities)** in Khordha District falls within the jurisdiction in Bhubaneswar Tahasil.

It is further certified that:

(a) *The complete process for identification and settlement of rights under the FRA has been carried out for the entire Ac.26.150 of forest area proposed for diversion. A copy of records of all consultations and meetings of the GramaSabha/Sub-Division Level Committee and the District Level Committee are enclosed as annexure 1 to annexure 3.*

(b) *The diversion of forest land for facilities managed by the Government as required under section 3 (2) of the FRA have been completed.*

(c) *The proposal does not involve recognized right of Primitive Tribal Groups and Pre-agricultural communities.*

Encl: As above

Signature
23/10/19
(Sitansu Kumar Rout)
DISTRICT COLLECTOR

Figure B1: Example Letter of Informed Consent between Gram Sabha and Developer

Note: Scanned letter from the District Forest Office of Odisha certifying the informed consent between the concerned Gram Sabha and the developer of a health facility involving forest diversion in Khordha District.

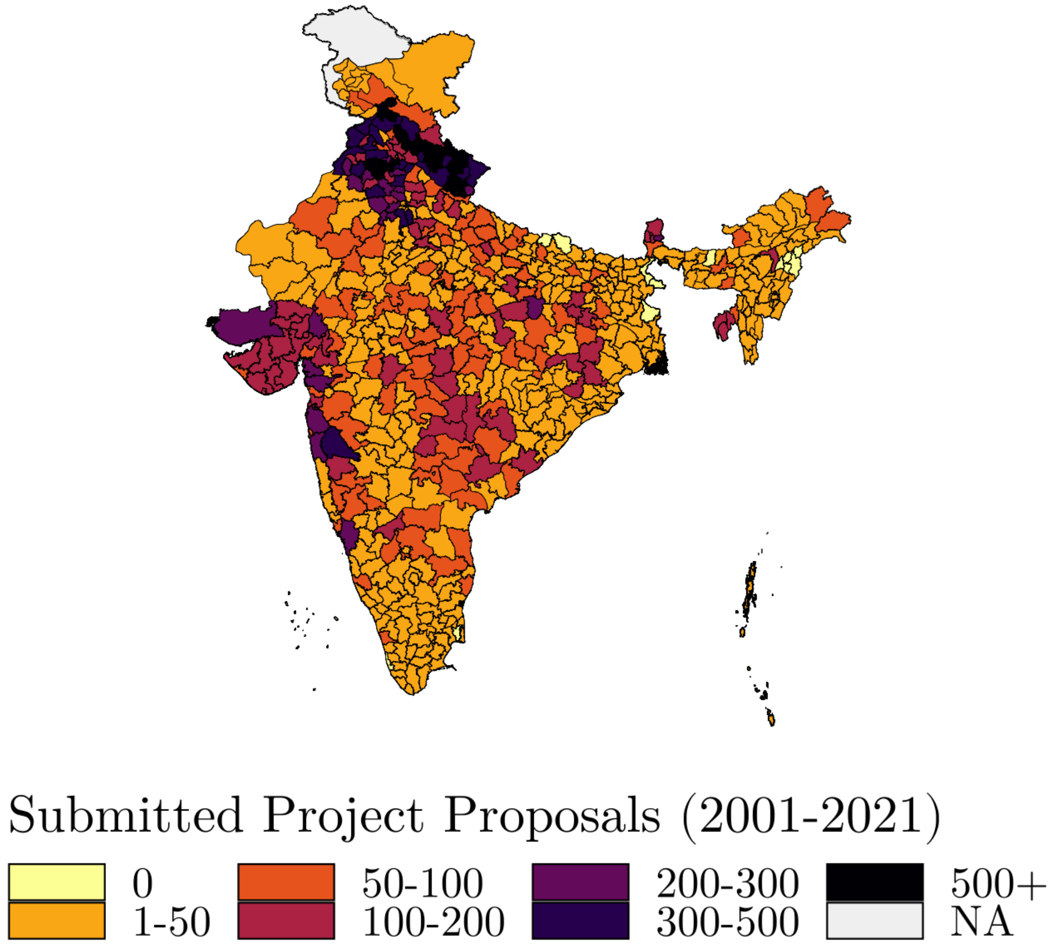


Figure B2: Submitted Proposals For Projects Involving Forest Encroachment

Note: Figure shows the total number of development project proposals submitted between 2003-2021. All development projects involve forest encroachment.

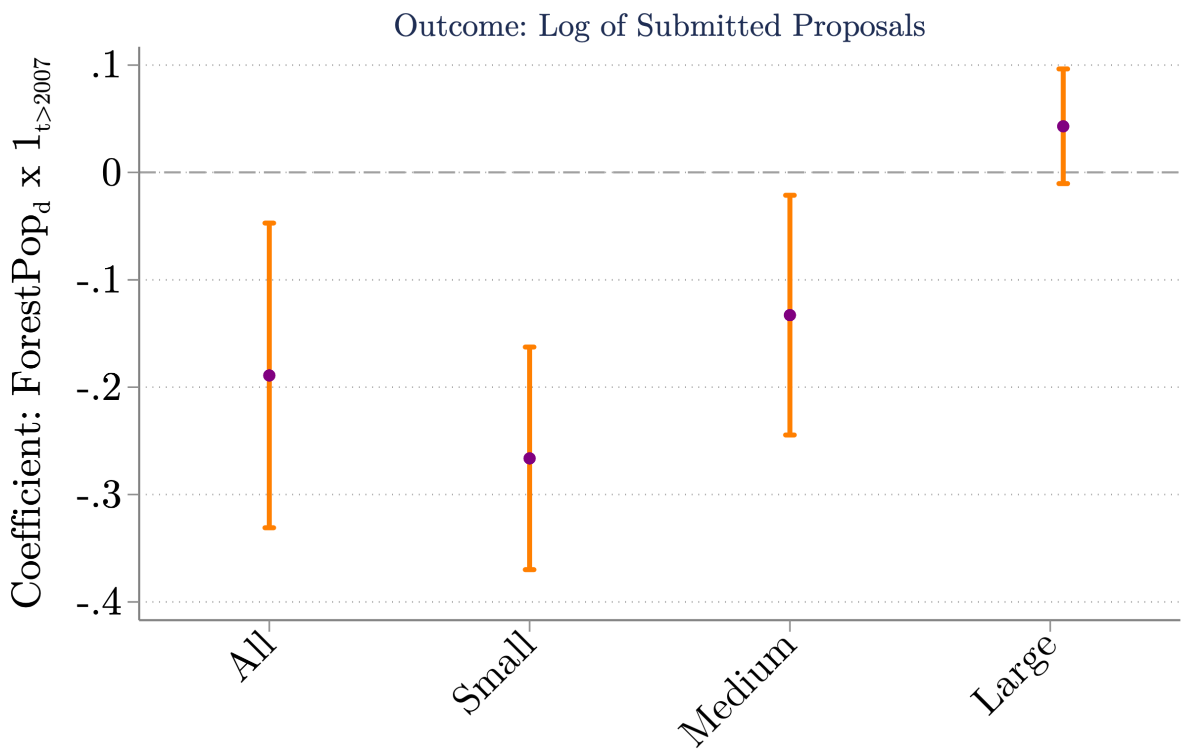


Figure B3: Difference in Difference Estimates by Project Size

Note: Data are at the district-year level. Dots are difference-in-difference coefficients from Equation 6 and bars are 95% confidence intervals. The outcome in the "Small" specification is log number of permits filed for small projects, which include transportation, services, and underground projects. "Medium" include other, irrigation, and electricity projects. "Large" include defence and mining. Standard errors clustered by district.

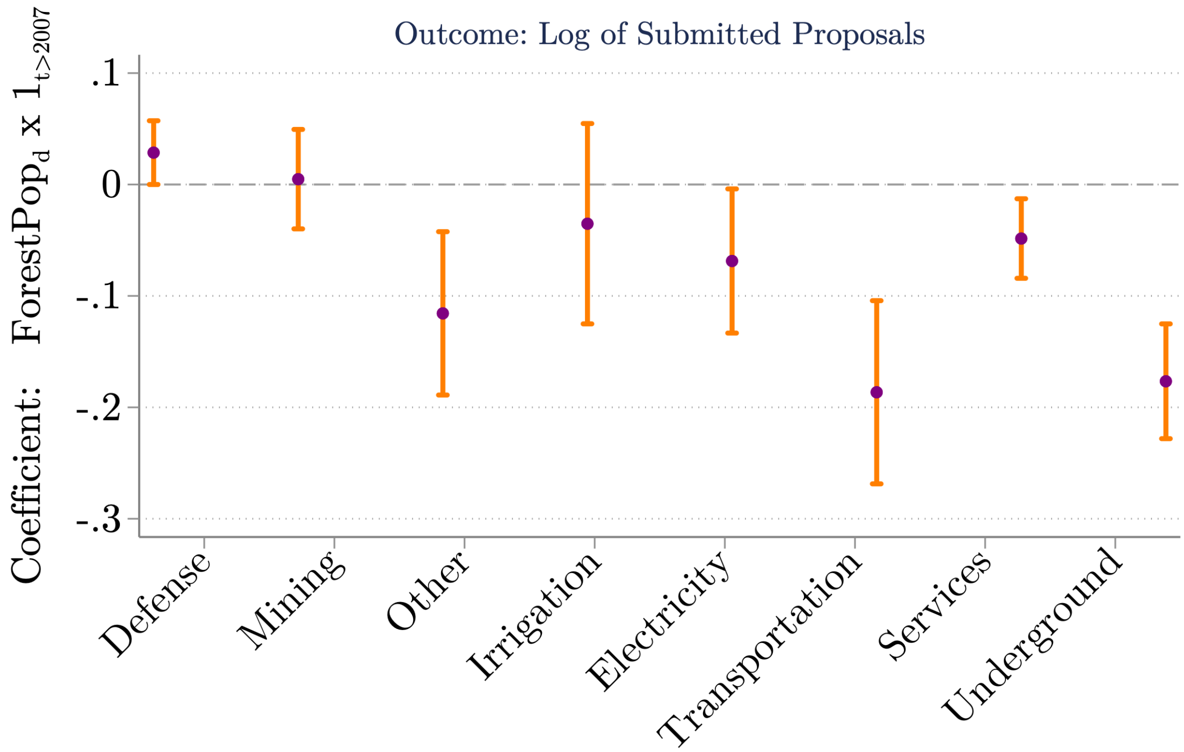


Figure B4: Difference in Difference Estimates by Category

Note: Data are at the district-year level. The outcome is log number of deforestation permits issued for a particular project category. Purple circles are coefficients from Equation 6. Bars represent 95% confidence intervals. Standard errors clustered by district.

C Data Appendix

C.1 Permit Data Construction

To obtain clearance for deforestation (which we refer to as a deforestation permit throughout the paper), firms submit a proposal to the District Forest Office through the *Forest Clearance* process—an ecological review that awards a permit for diverting forestland for non-forest use. We obtained the universe of submitted proposals from the PARIVESH portal, which reports project categories and district names.

Data cleaning and panel aggregation proceeds as follows. We first drop rejected projects (3.5% of sample) as well as projects where the year of submission occurs after the approval year (0.6% of projects), which likely reflects data entry errors.

Table A11: Procedure for Project Categorization

Raw Entry	Recategorized Entry
hydel, sub station, thermal, transmission line, village electricity, wind power, solar power	Electricity
road, railway, approach access	Transportation
canal, irrigation, drinking water	Irrigation
mining, quarrying, borehole prospecting, industry[18]	Mining
defence	Defence
school, dispensary, hospital	Services
optical fibre cable, pipeline	Underground
Everything else	Other

Note: The left column is the verbatim project categories as entered in application by the firm. The right column describes the synthesized categories for the purpose of simplifying project types.

We then consolidate project categories into eight groups according to Table A11. We also found many projects misclassified as "other" even though they fit into these categories. For these, we used project descriptions to reclassify "other" projects as follows: "other" projects containing the word "plant", "mine", or "quarry" are reassigned to Mining; projects with the word "railway" are reclassified as "Transportation"; "defence" or "army" to Defence; "power", "substation", "kV", or "transmission line" to Electricity; "oil", "gas", or "LPG pipeline" to Underground; and "water" or "irrigation" to Irrigation. "other" project descriptions with the words "school", "hospital", "college", "health", "safari", "airport", "office", "tourism", or "petrol pump" are reassigned to Services.

Next, we address the problem of district splitting and name changes. District names are an unstructured string with many spelling inconsistencies. We construct a consistent crosswalk to 2001 Census district codes in three steps. First, districts renamed after 2001 are reverted to their 2001 Census names. Second, districts created through post-2001 splits are reassigned to their original parent Census districts. These steps produce a stable geographic unit over time. Third, we fuzzy match district names and Census names using Levenshtein string distance, successfully identifying census codes for 98% of districts.

Lastly, we transform project-level records into a district-yearly panel. Since some projects span multiple districts (e.g. transmission lines), we first reshape the data from project to project-district level, where each row represents a project *component* falling into a given district. We then aggregate to the district-year level, constructing counts of permits for project components in each district and year, overall and category-wise (e.g. total deforestation in January 2018 for electricity projects in Delhi). Lastly, we balance the panel by assuming districts and time periods not in the portal had zero submitted proposals.

C.2 ASI Data Construction

We use establishment level data from the Annual Survey of Industries (ASI) covering 2003-2015. The ASI is collected by the Ministry of Statistics and Program Implementation (MoSPI), Government of India, and covers all registered industrial units that employ 10 or more workers and use electricity, or that employ at least 20 workers and do not use electricity. The sample frame includes a “census” survey, which is carried out every year, and a “sample” survey, which is carried out every few years. Relative to other Indian firm datasets, the ASI offers the widest and most detailed coverage of the registered manufacturing setor and is comparable to manufacturing surveys in the United States and other industrialized countries (Colmer, 2021).

A key data contribution of this paper is the construction of a harmonized firm panel with consistent firm and district IDs. We begin with a restricted access ASI version obtained under a MoSPI data agreement that includes consistent firm IDs but no district IDs. We merge this with a publicly available version of the ASI that contains district IDs but not consistent firm IDs. The merge is performed using exact matches on ten balance-sheet variables. This procedure successfully assigns district codes to roughly 80% of firms with consistent firm IDs in the restricted access ASI. The remaining unmatched firms were almost entirely ones surveyed in 2004 and 2009, which we drop from the analysis.[19] The final sample excludes firms that were closed in a given year.

After building the firm panel, we proceed to classify industry sectors. India uses the National Industrial Classification (NIC) coding system to classify industries. A challenge is that NIC codes change periodically during our sample period. We address this by using a concordance table provided by Murray Leclair (2025) to map all establishments into a consistent industry classification.

Lastly, we convert input and output values from nominal units (rupees) to real units. We first convert values to U.S. dollars and then deflate to real terms using product-specific price indices. Output is deflated using wholesale price indices (WPI) from the Office of the Economic Advisor. Because WPI industry categories do not align perfectly with NIC codes, we use the crosswalk from Martin et al. (2017) to assign appropriate deflators. Labor inputs are deflated using the Consumer Price Index (CPI) and capital stock is deflated using the WPI for capital goods. We are unaware of a dedicated land deflator for India and, therefore, deflate land using the capital deflator as in Sood (2023).

[19] Results are unchanged when we include the few matching firms from 2004 and 2009 (Section 6.2.2).

C.3 Validation with Satellite Forest Data

We use high-resolution satellite data on deforestation to validate our two key findings, that the FRA leads to (i) declining industrial land use near tribal forestland, and (ii) a shift in industry composition toward larger firms. Both effects have direct implications for forest cover, which provides critical ecosystem services to forest-dependent communities. Given that we document a sharp reduction in firms' demand for forestland (Table 1), we expect to observe corresponding declines in forest diversion on the ground.

We construct a deforestation metric, D_{dst}, using the Global Forest Change product (Hansen et al., 2013), which measures yearly forest loss at 30m resolution. We then extract total area deforested within district boundaries in each year and divide by land area. Following Equation 6, we estimate a difference-in-difference design at the district level:

$$D_{dst} = \varphi \cdot (ForestPop_d \cdot \mathbb{1}_{t>2007}) + \sigma \cdot (ForestPop_d \cdot \mathbb{1}_{t>2007} \cdot Large_d) \qquad (13)$$
$$+ \mathbf{X}'_{dst}\Omega + \alpha_d + \gamma_{st} + \epsilon_{dst}$$

Where d, s, and t index the district, state, and year, respectively. $Large_d$ is the mean of $Large_i$ from Equation 11 at the district level, capturing the share of large ASI firms in the district at baseline. Remaining terms are as previously defined. φ and σ are the coefficients of interest and capture the policy impact on deforestation in districts dominated by small and large firms, respectively. Since small firms contract land use and large firms expand (Table 2), we expect $\varphi < 0$ and $\sigma > 0$.

Results are shown in Table A9. The takeaway is that the average-versus-compositional distinction emerges in satellite forest imagery: while deforestation declines on average, this masks a pattern of intensifying forest loss in districts with larger firms. Column 1 reports standard difference-in-difference estimates. The FRA reduces deforestation on average, consistent with falling demand for forestland and lower land valuation near tribal forestland. Column 2 shows triple difference estimates from Equation 13. We find $\varphi < 0$ and $\sigma > 0$, consistent with the FRA inducing firm expansion among larger firms.

This validation exercise has three implications: first, it strengthens internal validity by showing that our findings from administrative data are echoed in independent satellite imagery. Second, the fact that forest loss is intensified in districts composed of larger firms matters ecologically. These forests provide critical ecosystem services as well as cultural value for millions of forest-dependent people. And third, intensified forest loss by larger industry implies heightened scope for land conflicts between developers and tribes, potentially reducing welfare. We turn to this topic next.