Decentralizing the Development-Conservation Trade-off: Evidence from Forestland Diversions in India*

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Abstract

We examine how decentralizing the approval authority for *legal* deforestation affects the trade-off between economic development and environmental conservation. Exploiting a policy reform in India that shifted the approval authority of projects between 20–40 Ha. from the central to state governments, we find that decentralization increased the volume of these applications, despite states being less likely to approve them. To rationalize these patterns, we develop and estimate a structural model of endogenous application and approval decisions using the *universe* of project-level proposals and their approval outcomes. Our estimates indicate that state governments place greater weight on economic development than the center, but applicants face significantly lower application costs under them as well, leading to more — but lower-quality — proposals. This results in the state behaving in a more pro-*conservation* way than the center. This pattern is more pronounced in more corrupt states with even lower application costs, and less pronounced in states with higher forest cover, where state preferences are fundamentally more pro-conservation. In the aggregate, decentralization modestly increases deforestation (driven by higher application volume) while slowing local economic development (due to lower application quality).

JEL Codes: Q58, Q23, D73, O13
Keywords: Legal deforestation, Decentralization, Environmental Governance

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1 Introduction

As countries pursue economic growth, they are increasingly confronted with the challenge of balancing development objectives with environmental sustainability. This trade-off is especially salient in low- and middle-income countries (LMICs), where the need for infrastructure, industry, and livelihoods coexists with growing concerns over climate change, biodiversity loss, and forest degradation.[1] Understanding how institutional structures and decision-making processes shape the incentives and behavior of various stakeholders is central to determining how this trade-off ultimately gets resolved.

In this paper, we examine how decentralizing the decision-making authority over *legal* deforestation — specifically, the approval of projects that divert forestland for economic purposes — affects the development-conservation trade-off. While decentralization may, in theory, improve alignment between policy decisions and local preferences, it can also alter the behavior of applicants and the types of projects that are approved, with first-order aggregate implications for both environmental outcomes and economic development. Decentalizing the decision-making process therefore introduces a number of new considerations. Regional governments, with closer proximity to local needs and conditions, may weigh conservation differently than the central government. On the other hand, applicants may face lower costs in navigating the local bureaucracy (e.g., due to geographic proximity, better knowledge of procedures, or greater informal access), which could increase application rates, particularly of lower-quality projects. Together, this suggests that that decentralization may influence both how many (volume) and which projects (quality) get proposed and approved.

Several studies in the literature have examined the impact of decentralization on environmental policy-making. For example, Burgess et al. (2012) examine impact of decentralization on illegal deforestation in Indonesia, Lipscomb and Mobarak (2016) on water pollution in Brazil, and Edmonds (2002) and Somanathan et al. (2009) on forest conservation in Nepal and India respectively. However, these studies focus on contexts where any form of resource extraction (deforestation or water pollution, for example) is either illegal or undesired, providing a clear objective for the government to reduce it. In contrast, our setting examines *legal* forestland diversion, where projects are often economically desirable, thus providing a unique setting to study how different tiers of governance weigh development benefits against environmental costs, when both sides of the trade-off are meaningful.

A policy reform in India offers a unique setting to study this question. Under Indian law, any development project that requires the diversion of forest land must obtain approval from the government. Whether the approving authority is a state or central government depends on the area of forestland to be deforested i.e., the "size" of the project. Traditionally, smaller projects (with area less than 20 hectares (Ha.)) were approved by state governments, while those above 20 Ha. were approved by the center. A policy reform in 2004 doubled this size threshold to 40 Ha., which increased the share of projects assessed by state governments from 43% to 75%.

[1] See Lawrence and Vandecar (2015), Konikow and Kendy (2005), Shukla, Nobre and Sellers (1990).

This significant institutional change in the approving authority allows us to examine how it influences the pattern of applications and approvals for forestland diversion, along with their aggregate impact on forest cover and economic development.

To study this, we compile the *universe* of applications submitted to the Indian government for diverting forest land between 1990-2019. Spanning a period of three decades, these data contain rich project-level information on the size of land proposed for diversion, location, sectoral purpose, intended economic activity, and most importantly, the approval outcome. Given the establishment of a National Green Tribunal in 2010, which opened the window for citizens to challenge the governments' forestland diversion decisions, we restrict attention to applications during 1990-2009 for our main analysis. We also restrict our sample to projects between 10-100 Ha., where the decision-making tier of government was directly affected by the reform, and where application procedures remained relatively consistent. For example, the outcome of very small projects (below 5 Ha.) is directly decided by local Indian Forest Service bureaucrats, while projects over 100 Ha. involve additional paperwork, scrutiny, and inspections.

We begin by establishing two key empirical results. First, decentralizing the approving authority (for projects between 20-40 Ha.) increased the number of applications received by states. We show this in two ways: first, we document a clear upward shift in the CDF of application sizes in the 20–40 Ha. range in the post-2004 period, with no comparable shift for projects below 20 Ha. We also find a discontinuous increase in application density just below the threshold that determined the approving authority — 20 Ha. before the reform and 40 Ha. after — suggesting that some applicants strategically reduced their project size to be directed towards states for approval. In contrast, there is no discontinuity at 40 Ha. (20 Ha.) pre-2004 (post-2004).

Second, we document, that despite receiving more applications, state governments (viz-a-viz the center) were *less* likely to approve projects on average. Using a difference-in-differences framework, we find that the average approval probability of projects between 20-40 Ha. (relative to those below 20 Ha.) *fell* by 8-9 p.p. (around 15%) after the policy reform.[2] Taken together, this pattern — more applications and a lower approval rates — suggests a change in the *quality* of projects that were applied (and hence approved) after decentralization.

To explain these patterns, we develop a dynamic model in which every period, applicants decide whether to apply based on expected benefits and application costs, and governments decide whether to approve based on a welfare trade-off between economic value and conservation. In the model, each project is characterized by its size (S) and quality (z), the latter being observable to the government, but not to the researcher. When deciding to apply, an applicant trades-off the expected net benefit from the project, taking into account the approval probability that is endogenously determined in equilibrium, with a (government-specific) cost of application (denoted by λ_g). On the other hand, the key decision faced by a government $g \in \{\text{Center, State}\}$ in making its approval decision is the period-specific weight (b_{gt}) that it

[2] As we discuss in Section 3, this result is robust to dropping projects close to the policy threshold given the endogenous sorting around these thresholds.

puts on the economic value of the project $\{S, z\}$ relative to the cost of deforesting it. The government is guided by its fundamental welfare weight ω_g on economic development in making its decision. However, it also takes into account how application costs affect the quality of applications and hence, the economic benefit from approvals. The model thus generates equilibrium predictions about the volume, quality, and approval of applications, based on differences in ω_g and λ_g across the two tiers of government (state and center).

The policy reform in 2004 allows us to estimate these structural parameters. Intuitively, because the *same* class of mid-sized projects (20–40 Ha.) switched from central to state approval, we can compare pre- and post-reform distributions of applications and approvals (after adjusting for time trends) to identify how differences in preferences and application costs can explain the observed outcomes. In particular, we recover the relative welfare weights that state governments put, relative to the center, on the economic value of projects (vis-a-vis conservation) i.e., $\omega \equiv \omega_{state}/\omega_{center}$, and the relative cost of application under the two i.e., $\lambda \equiv \lambda_{state}/\lambda_{center}$. Additionally, we show that under our parametric assumptions, the optimal period-specific weights on development b^*_{gt} are such that their ratio is constant over time, i.e., $b^* \equiv b^*_{state,t}/b^*_{center,t}$. We identify and estimate b^* and show that it is related to our estimates of ω and λ in ways as predicted by our model.

We estimate $b^* = 0.89$, which implies a 11% decrease in the approval probability for a given project of quality z and size S, *conditional* on applying. In other words, it reflects a higher weight on forest conservation relative to development by states relative to the center. A second channel speaks to the lower cost of application (λ) that along with b^*, drives the selection of applied projects. We estimate $\lambda = 0.85$, implying that applicants face 15% lower costs when applying to states as opposed to the center. These two forces push in opposite directions: a lower b^* reduces approval rates and hence applications — a "conservation effect", while a lower λ increases applications — a "selection effect". Our quantitative estimates indicate that the selection effect dominates ($\lambda < b^*$), resulting in an increase in the volume of applications (18%), despite a lower approval probability (13%), and a modest 3% net increase in deforestation. This is consistent with our estimate of $\omega = 1.02$, implying that states have a higher fundamental welfare weight on development compared to the center. Therefore, states in spite of being more pro-development than the center, behaves more pro-conservation than the center, due to the lower application costs and the associated lower quality (and higher volume) applications it receives.

We validate the analysis in three ways. First, we show that the model-implied drop in approval probability is close to the empirically observed reduced-form estimates from the difference-in-difference specifications (Section 6.1). Second, using post-2014 application data that reports the expected employment that a project generates, we show that state-approved projects expect to generate lower employment levels — a proxy for economic value — relative to centrally approved projects of similar size (Section 6.2). Third, we show that decentralization increased the time taken to approve projects, especially mid-sized ones, by around 3-4 months (15-20%). This is consistent with states facing a larger and more heterogeneous applicant pool (Section 6.4).

As a further validation of our quantitative estimates, we explore in Section 6.3 whether the structural estimates (that reflect differential government preferences and application costs) are correlated with institutional characteristics and forest endowments across states. To begin, we classify states into above- and below-median categories based on measure of municipal corruption in them. We then re-estimate our model separately for these two groups of states. We find that applicants in above-median corrupt states face significantly lower application costs than those in less corrupt states. The estimates of ω across both categories of states, on the other hand, are statistically indistinguishable from each other. Additionally, the estimates of b^* follow the opposite pattern of λ which suggests that corruption's effect on state's approval behavior operates primarily through a reduction in application costs, as opposed to altered preferences for conservation of these states. The opposite is true when we examine variation by baseline forest cover (a proxy for citizen's preference for conservation). We estimate a stronger preference for conservation i.e., lower ω, in states with above-median baseline forest cover as compared to below-median ones. Meanwhile, application costs (λ) are similar in either category of states. Taken together, this suggests that the same reform can lead to very different outcomes in places with different local governance, and local preferences for environmental conservation.

In Section 7, we examine whether these micro-level changes translated into meaningful aggregate impacts. Using a district-level panel data on forest cover and nightlights, we show that districts with greater exposure to decentralization (i.e., those with a higher fraction of mid-sized projects prior to 2004) experienced a larger increase in applications, but no significant decline in forest cover. However, they did experience a significant slowdown in nightlight growth, a widely used proxy for local economic activity. These patterns are consistent with the quantitative implications of the model discussed above — while overall deforestation increased only modestly, there was an increase in lower-value projects getting approved under states, potentially slowing economic growth. Thus, while decentralization can lead to more stringent decision-making, it may not yield better development outcomes if it changes the composition of applications.

The last part of the paper (Section 8) extends the baseline model to allow strategic manipulation of project size around the policy threshold. Given that we see bunching of applicants at the policy thresholds as discussed earlier, we explicitly consider the potential for applicants to strategically manipulate project sizes around policy thresholds (i.e., "sorting"), in addition to the "selection" effects. Quantitative estimates suggest that sorting accounted for only 13% of the observed changes in applications around the threshold, with the rest coming from selection.

In sum, our findings show that decentralization changes both who applies and who approves. Even when states have stronger conservation preferences, the lower cost of accessing them leads to more—but lower-quality—projects. This not only reduces the quality of economic development, but also attenuates the intended gains from environmental regulation. Effective decentralization must account not only for governmental preferences, but also for how policies shape the incentives and composition of those who engage with the system.

Our paper contributes to several strands of the literature. Researchers and policymakers are increasingly studying reciprocal relationship between economic development and the environment (Liu, Shamdasani and Taraz 2023, Jayachandran 2022, Garg and Shenoy 2021), contributing to debates in LMICs about sustainable ways of achieving economic growth, as well as understanding how stakeholders respond to these tradeoffs (Kala 2017, Jack, Jayachandran, Kala and Pande 2022). We contribute to this discussion by focusing on the governance framework surrounding environmental sustainability in the context of deforestation shapes this trade-off. With regard to the effect of decentralization on forest conservation, while Edmonds (2002) and Somanathan, Prabhakar and Mehta (2009) find positive effects of decentralization on conservation, Burgess, Hansen, Olken, Potapov and Sieber (2012) report greater deforestation due to increase in number of local districts. Harstad and Mideksa (2017) reconcile the conflicting empirical findings by arguing theoretically that whether decentralization leads to more or less conservation can depend on the strength of the property rights regime. We contribute by pointing out that the effect of decentralization is also contingent upon the local characteristics of jurisdictions, such as stock of forest, and political linkages between governance tiers. Several papers highlight the importance of governance structure and policy regimes in shaping deforestation. Burgess, Costa and Olken (2019), for example, show how changes in the regulatory regimes in Brazil led to significant differences in illegal deforestation in the Amazon. Araujo et al. (2020) examine how spatially differentiated tax policy can mitigate inefficient deforestation in Brazilian Amazon by making individual farmers internalize the social cost of deforestation. Hsiao (2021) shows how coordinated import tariffs can effectively substitute domestic regulation in controlling the expansion of palm oil plantation in Indonesia and Malaysia, an important source of deforestation in the region. These studies examine the decision of individual farmers to divert land from forest to agriculture. Our work highlights the role of government in mediating this decision in the context of economic activities more generally, and how the decisions of individuals and governments across tiers interact.

Our work also relates to the effect of decentralization on various governance outcomes such as local public good provision (Kis-Katos and Sjahrir 2017, Gadenne and Singhal 2014, Bardhan 2002), resource utilization (Gadenne 2017), corruption (Fan et al. 2009), and specifically, management and utilization of natural resource, such as forest (Baland et al. 2010, Lund and Treue 2008, René Oyono 2005) and water (Das and Dutta 2023, Jacoby et al. 2021, Drysdale and Hendricks 2018). Several of these studies examine local management of natural resources at the level of districts or lower, while we focus on devolution of governance responsibility from the national to the regional government in a context where governments balance conservation with development goals. Researchers typically estimate the effect of decentralization by either exploiting some policy reform that transfers the responsibility of policy implementation completely from a higher to a lower tier (Jacoby et al. 2021), or using over time proliferation of local jurisdictions, i.e., horizontal decentralization (Burgess et al. 2012, Lipscomb and Mobarak 2016), or increase in number of governance tiers, i.e., vertical decentralization (Fan et al. 2009). In our context, degrees of both vertical and horizontal decentralization are kept the same, while the responsibility of a specific policy is *partially* shifted from the higher to the lower tier that creates variation in responsibility *within* a local jurisdiction (i.e., state).

2 Context and Data

2.1 Deforestation and Economic Development in India

India faces significant challenges in managing forest resources due to competing demands of economic growth and environmental conservation. Sudhakar Reddy et al. (2016) document a 28% loss in forest reserves between 1930 and 2013, primarily driven by activities related to economic development. For example, Ranjan (2019) estimate that a third of forest loss in a district between 2001-14 relates to mining activities involving coal, iron ore, and limestone. Similarly, infrastructure projects, notably highways, have also been significant contributors to local forest loss (Asher et al. 2020).

While illegal logging and forest encroachment continue to contribute significantly to deforestation, *legally authorized* forest diversions for development projects are equally important policy concerns. Ghosh (2016) reports that, over the past three decades, roughly 14,000 km² of forestland—approximately 2% of India's forest stock—has been officially cleared by government-approved projects. This magnitude of this legal forest diversion rivals the forest loss attributed to illegal encroachments discussed earlier. In this paper, we specifically investigate differences in how central and state governments evaluate applications for *legal* forestland diversions and the resulting implications for both deforestation outcomes and economic development.

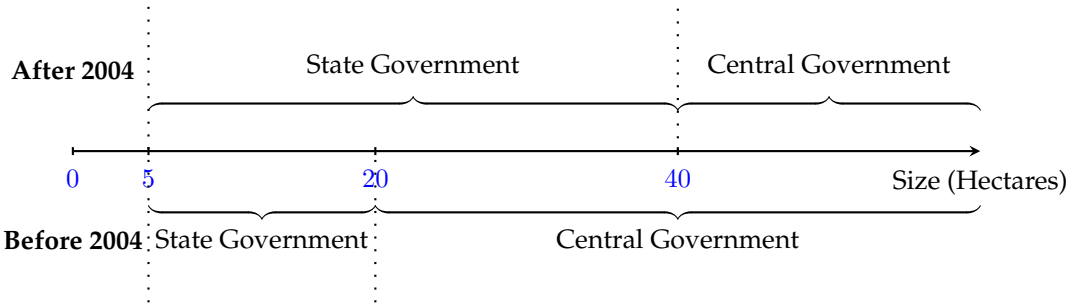
2.2 Background and Institutional Details

All forest land in India are state property. Any development project, such as road and railway construction, canal irrigation, establishment of educational or medical facilities, etc. that requires the diversion of forest land must first secure governmental approval. The institutional framework and procedures governing this approval process were established under the Forest Conservation Act of 1980. Under this Act, the authority responsible for approving forest diversion projects (either the central or state government) is determined by the size (in hectares) of the land parcel proposed for diversion.

All applications for forestland diversion are first submitted to the District Forest Officer (DFO) of the district where the proposed project is located. Following preliminary inspections, the DFO forwards the application to the relevant ministry at the state government level, which conducts further assessments and forwards it to the respective Regional Office, typically located in the state's capital. Decisions on very small projects — with size below 5 hectares (Ha.) — are directly made by a senior Indian Forest Service bureaucrat at the Regional Office.

Prior to 2004, projects ranging from 5-20 Ha. were decided by a state-level committee at the Regional Office, consisting of Indian Forest Service officials and state government representatives. Projects exceeding 20 Ha. were forwarded by the Regional Office to the Ministry of Environment, Forest, and Climate Change (MEFCC) at the central government level for the

Figure 1—Approving Authority as a Function of Project Size



Notes: The above figure shows the approving authority for each size of project. The horizontal axis reports the size in hectares, while the dotted lines show the thresholds for approving authority before and after the 2004 amendment.

final decision. However, in 2004, an amendment raised the central government's approval threshold from 20 Ha. to 40 Ha. Consequently, state governments gained final approval authority for projects ranging between 20-40 Ha., significantly expanding their decision-making power. We illustrate these rules and their amendment in Figure 1.

Importantly, the process of obtaining approval for forest diversion is not costless for applicants. Preparing an application involves substantial paperwork that includes detailed project maps, comprehensive tree surveys, and thorough project descriptions. Additionally, the approval process is lengthy, frequently taking over a year. These factors imply that the cost and complexity associated with the application process significantly influence applicants' decisions regarding whether and how to apply.

2.3 Data

Our primary source of data come from the Ministry of Environment, Forest and Climate Change (MEFCC) and contain the *universe* of applications submitted to the Indian government for forestland diversion between 1980 and 2019. These data provide extensive details about each project proposal. Specifically, each application includes information on the area (size) of forestland proposed for diversion, geographic location (state and district), the intended economic purpose of the project (e.g., irrigation, road construction, mining), the date of application, various stages of the approval process, and the final decision (including the approval date if approved).

Our main analysis focuses on applications submitted during 1990–2009 involving land parcels between 10 and 100 Ha. We restrict our sample to this period because, before 1990, procedures under the Forest Conservation Act were not consistently implemented. After 2009, the establishment of the National Green Tribunal (NGT) in 2010 allowed citizens to legally contest governmental decisions on forest conversions, potentially affecting application and approval behaviors differentially by central and state governments.

We restrict our attention to projects between 10 Ha. and 100 Ha. As we describe in Section 2.2,

the approval decisions for very small projects below 5 Ha. were made by a different administrative mechanism. As shown in Figure A1, there is a significant discontinuity in the density of applications received at this threshold that is unrelated to the policy of interest in this paper. Therefore, we ignore these small projects (below 10 Ha.). Additionally, we exclude projects over 100 Ha. as they involve a more complex application procedure requiring additional paperwork and inspections.

2.4 Descriptive Statistics

Our final sample consists of 3,111 projects with an average (median) project size of 32.3 Ha. (24.4 Ha.). Figure 2a shows the distribution of project size across all projects in our sample. The density of size falls quickly as size increases. Figure 2b shows that the average number of applications received each year increased from 130 to 215, before and after the policy reform. This is also reflected in more applications being approved each year, which increased from 94 to 165 applications. From Appendix Figure A2, we see a similar increase in the average area of forestland that is proposed (4,200 Ha. to 7,000 Ha.) and approved (3,100 Ha. to 5,400 Ha.) for deforestation each year as well.[3] Before discussing the approval probabilities, we examine heterogeneity across the types of projects as well as regional coverage across Indian states.

Across Project Categories: We categorize projects into five categories, namely: (i) infrastructure projects, such as roads, railways, transmission lines, etc.; (ii) irrigation projects, such as canals; (iii) projects related to natural resources, such as hydel, thermal, and wind energy generation, and mining; (iv) health and education projects, such as schools, hospitals, provision of drinking water, etc.; and (v) other projects without a clearly defined economic purpose.

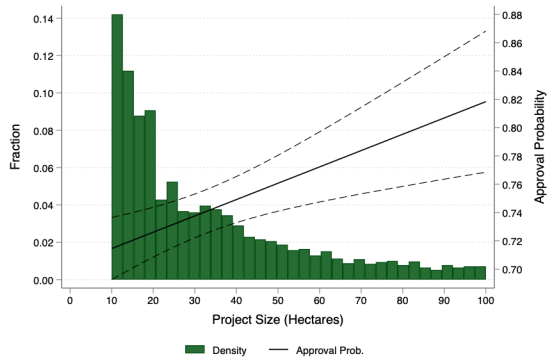
From Figure 2c, infrastructure, irrigation, and natural resource projects each accounted for around 25-30% of the total number of applications prior to the policy reform. Non-specific "other" projects accounted for around 13%, with health and education related projects accounting for around 1.5% of projects. After the policy reform, we see around a 17 percentage points (p.p.) increase in the share of applications related to infrastructure, with a corresponding 12 p.p. and 5 p.p. decrease in the share of applications related to irrigation and natural resources respectively.[4]

Across Regions: Figure 2d then shows the distribution of these projects across different regions of the country (see Table A1 for the classification) over time. Prior to the policy reform, around a third of the applications come from the northern states, a quarter each from the western and southern states, while the rest (around 15%) from the southern states. These patterns

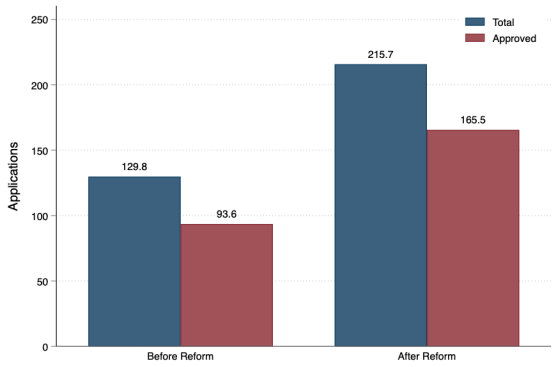
[3] Figure A2a and A2b show the total and approved number of application for each year separately, while Figures A2c and A2d show the total and approved area deforested each year respectively.

[4] Appendix Figure A3a show a similar pattern with total area proposed. Figures A4a and A4b then show these patterns for each year separately.

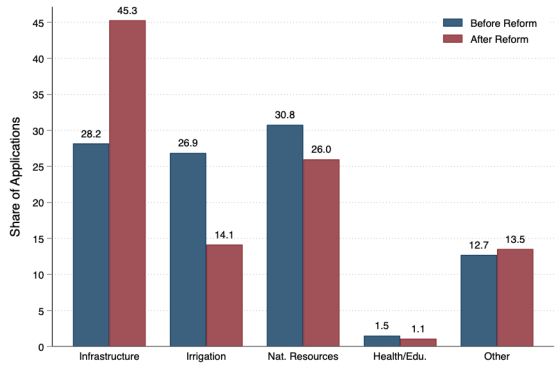
Figure 2—Descriptive Patterns of Project Applications



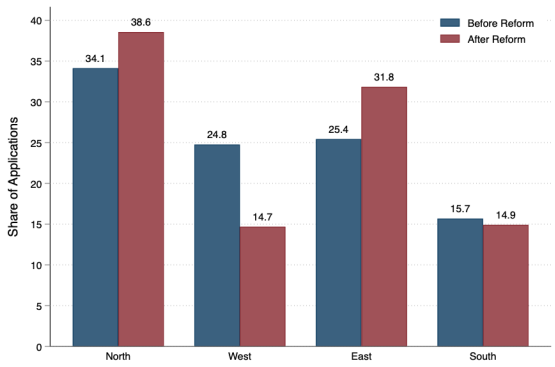
(a) Project Size Distribution



(b) Average Number of Applications



(c) Avg. Applications by Types of Projects



(d) Avg. Applications Across Regions

Notes: The sample is all projects between 10-100 Ha. between 1990-2009. Figure (a) shows the distribution of projects across the entire sample with a linear fit of the approval probability (solid line) and its 95% confidence interval (dotted lines). Figure (b) shows the average number of applications per year that were submitted (blue) and approved (red) before and after the 2004 reform. Figures (c) and (d) then show the percentage share of these applications across different project categories (Figure c) and regions (Figure d) respectively.

remain relatively more stable after the policy reform as well. Perhaps the largest change is a 10 p.p. decline in applications from the western states, with around a 5 p.p. each increase in applications from the north and east.[5]

Probability of Approval: Lastly, we now examine the probability of approval. We do so in multiple ways. First, from Figure 2a, the probability of approval varies distinctly as a function of project size (see secondary vertical axis on the right). While on average 75% of projects are approved, the approval probability is increasing in size, going from about 70% for smallest projects in the sample to about 82% on average for the largest. Second, looking before and after the policy reform from Figure 2b, the approval probability increases slightly from 72% before the policy reform, to around 77% after. Third, across project categories (see Appendix Figure A3c), infrastructure-related projects are more likely to be approved (83%), and projects in the "other" category are least likely to be approved (60%). These rates do not change much across

[5]Appendix Figure A3b show a similar pattern with total area proposed. Figures A4c and A4d then show these patterns for each year separately.

most major project categories after the policy reform either. Lastly, across regions, approvals rates are fairly constant around 70-75% both before and after the policy (Figure A3d).

3 Impact of Decentralization: Reduced Form Results

We leverage the 2004 policy reform described above — that shifted the approval authority for mid-sized projects (20-40 Ha.) from the central government to state governments — to examine how decentralization affects two key outcomes: (i) the volume of applications received; and (ii) the probability of project approval. This analysis helps motivate our theoretical framework and structural estimation approach presented in subsequent sections.

Categorization of Projects By Size: For the rest of the paper, we classify each project (based on its size) into the following groups: "small" projects of size less than 20 Ha.; "middle" size projects between $(20, 40]$ Ha.; and "large" size projects over 40 Ha. Clearly, these classifications are relevant from the perspective of the policy change: the approving authority for small and large projects was always the state and central governments respectively, but changed from the central to state governments for mid-sized projects after the policy reform in 2004. We summarize this in Appendix Table A2.

Using this classification, we examine the impact of decentralization on the number of applications and approvals in two ways: first, we examine the sorting of projects across the policy-relevant threshold (40 Ha.) in a regression discontinuity framework. However, given that the policy reform impacted all projects between 20-40 Ha., we then estimate a difference-in-difference specification to examine the impact of the policy more broadly. Both sets of analyses offer distinct insights regarding the application and approval process that we discuss subsequently.

3.1 Volume of Applications

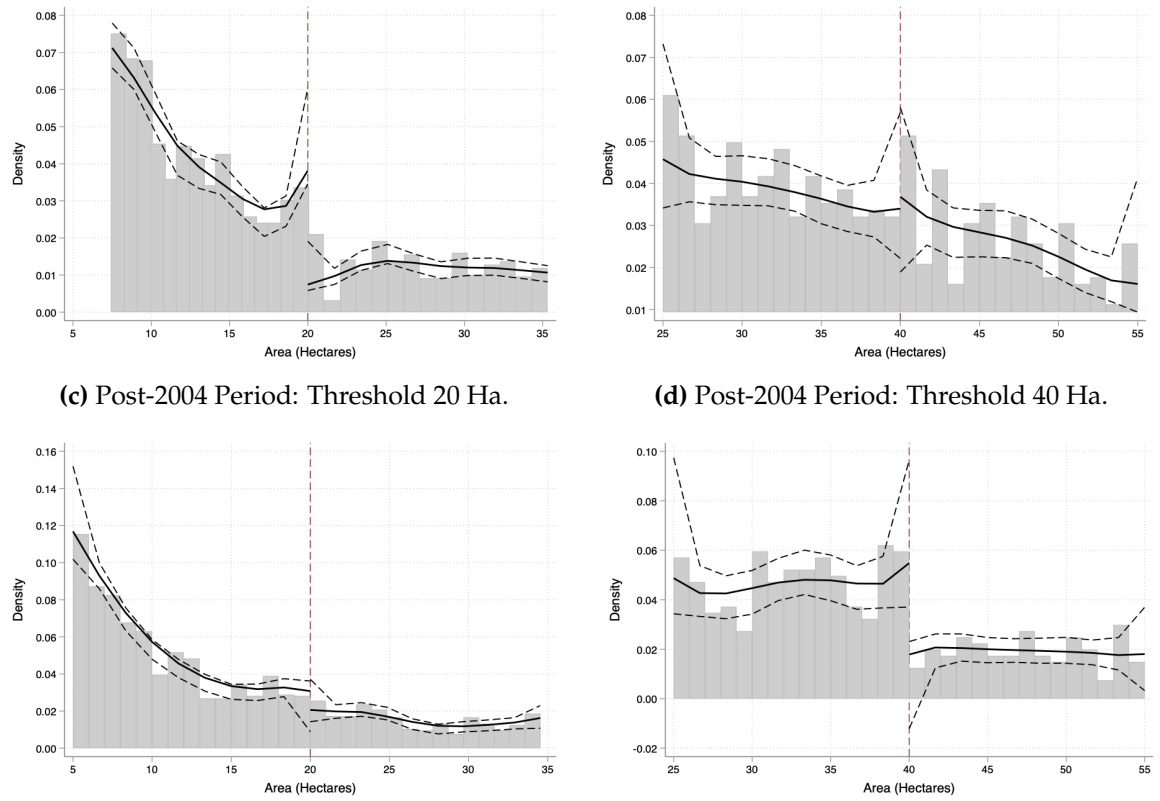
We first examine how the change in approval authority (from center to state) impacted the volume of applications.

Change in the Application Density Around Policy Thresholds. We start by examining whether decentralization influenced applicants' decisions to strategically manipulate project size to remain below the new threshold. Figure 3 shows results from McCrary density discontinuity tests conducted around the 20 Ha. and 40 Ha. policy thresholds, comparing the density of applications before and after the policy reform (in 2004). Prior to the reform, we find a sharp discontinuity in the density of applications at 20 Ha. (Figure 3a, p-value = 0.00), implying that state governments received significantly more applicants around the policy threshold as compared to the center. As expected, there was no discontinuity in the application density at 40

Figure 3—Density of Applications Around the Policy Thresholds

(a) Pre-2004 Period: Threshold 20 Ha.

(b) Pre-2004 Period: Threshold 40 Ha.



(c) Post-2004 Period: Threshold 20 Ha.

(d) Post-2004 Period: Threshold 40 Ha.

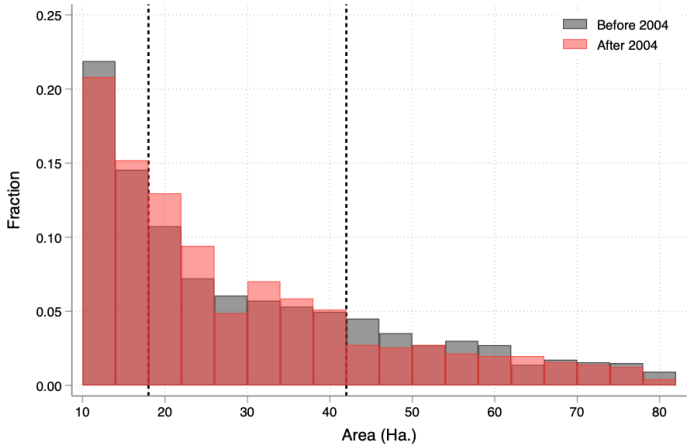
Notes: The above figure shows the McCrary density plot for the number of applications received around the policy relevant thresholds. Figures (a) and (b) report the density of applications in the pre-2004 period around the 20 Ha. and 40 Ha. thresholds respectively. Figures (c) and (d) report the density of applications in the post-2004 period around the 20 Ha. and 40 Ha. thresholds respectively. The dotted line report the 95 percent confidence interval.

Ha. in the pre-reform period (Figure 3b, p-value: 0.73). The policy reform moved the threshold size from 20 Ha. to 40 Ha. Consequently, we see that the discontinuity in the density of applications also moved to 40 Ha. post 2004 (Figure 3d, p-value: 0.00). Meanwhile, the previously observed discontinuity at 20 Ha. entirely disappears post-reform (Figure 3c, p-value: 0.98).

Impact on Applications Between 20-40 Ha. While the above analysis points to the sorting of projects around the threshold, the policy in fact impacted all projects more broadly between 20-40 Ha. In Figure 4, we plot the fraction of projects across the *entire* size distribution, specifically comparing the density of applications before and after the 2004 policy reform. We see a clear increase in the density of applications for areas targeted by the policy i.e., between 20-40 Ha., when the approving authority moved from the center to state governments. We formalize this by estimating the following difference-in-differences specification:

$$\begin{aligned} \mathrm{Y}_{it} &= \alpha + \beta_1 \mathrm{Middle}_i + \beta_2 \mathrm{Middle}_i \times \mathrm{Post}_t \\ &+ \beta_3 \mathrm{Large}_{it} + \beta_4 \mathrm{Large}_i \times \mathrm{Post}_t + \mathrm{F.E.} + \varepsilon_{it} \end{aligned} \tag{1}$$

Figure 4—Density of Applications by Size Before and After the Policy Reform



Notes: The above figure plots the density of application across the area distribution before (black) and after (red) the policy reform. 20 Ha. and 40 Ha., the relevant policy thresholds are denoted by the vertical lines.

where Y_{it} is the CDF value for a project i of a category c, located in state s, and applied in year t. $Middle_i$ and $Large_i$ are dummy variables that take the value 1 if the project i is in the middle or large category as defined above, or 0 otherwise. $Post_t$ takes value 1 for year 2004 onward and 0 otherwise. Our coefficient of interest is β_2, which estimates the difference in the CDF value for a mid-size project (relative to a small-size one) before and after the policy. We cluster standard errors at the state and category level, to allow for the size of projects to be correlated either within broad categories (like infrastructure, irrigation, etc.) or across states.

Table 1 reports the results. Column 1 includes state-category fixed effects along with a post-reform dummy to control for general time-invariant characteristics before and after the policy reform. Column 2 additionally includes year fixed effects, absorbing all aggregate changes common across states and categories over time. Column 3 provides our most stringent specification, controlling for state-category-year fixed effects. These fully account for unobserved heterogeneity within state-category bins over time that might impact the decision to apply. In other words, identification is driven by the change in the size distribution impacted by the policy, as opposed to aggregate changes in state and project-category pairs over time.

Turning to the results, we see from Column 1 that the coefficient on Post is both quantitatively small and statistically insignificant at conventional levels, indicating no change in the CDF value for small-sized projects before and after the policy. On the contrary, there is a consistent 2 p.p. increase in the CDF value for mid-size projects after the policy reform (estimate for β_2), which is stable in magnitude and statistical significance as we add additional fixed effects across Columns 2-3. Lastly, note that since the CDF is a monotonically increasing function, an increase in the CDF value of mid-sized projects would automatically increase the CDF values for large-size projects as well, which is consistent with what we observe in Table 1.

Discussion. The above analysis provides several insights to understand the impact of the policy. First, there is an increase in applications made when the decision making process is

Table 1—Impact of the Policy Reform on the CDF of Applications

	Cumulative Density Value		
	(1)	(2)	(3)
Post	-0.01		
	(0.00)		
Middle	0.35***	0.35***	0.34***
	(0.01)	(0.01)	(0.01)
Large	0.63***	0.63***	0.62***
	(0.01)	(0.01)	(0.01)
Middle × Post	0.02**	0.02**	0.02*
	(0.01)	(0.01)	(0.01)
Large × Post	0.03***	0.03***	0.03***
	(0.01)	(0.01)	(0.01)
Mean—Small,Pre	0.22	0.22	0.22
R2	0.88	0.89	0.91
N	3060	3060	2575
State x Cat. FE	Yes	Yes	No
Year FE	No	Yes	No
State x Cat. x Year FE	No	No	Yes

Notes: The dependent variable is the CDF value for the size proposed for each project separately before and after the policy reform. All projects with area 10-100 Ha. are in the sample. The time period is 1990-2009. Middle is a dummy that takes value one if the project area is between 20-40 Ha., and Large if it is between 40-100 Ha. Post is an indicator for years 2004 and after. Column (1) includes state-category fixed effects, while Column (2) adds year fixed effects. Column (3) has state-category-year fixed effects. Standard errors are clustered at the state-category level. *** p<0.01, ** p<0.05, * p<0.1.

decentralized to states. This is reflected both in around the policy threshold, but also more broadly across the 20-40 Ha. distribution. Second, this increase cannot be explained by the selection of projects that are driven by changes in specific project categories in particular states over time. This points to more fundamental factors that impact the decision to apply, which motivates the need for a theoretical model that we will formalize in Section 4 later.

3.2 Probability of Project Approval

We now examine the implication of decentralization on the probability of approving projects. We estimate Equation (1) where the outcome is now a binary variable that takes the value 1 if a project i (in state s and category c) was approved and 0 otherwise. Our coefficient of interest (β_2) now estimates the difference between the average approval probabilities under central (in the pre-period) and state government (in the post-period), for the mid-sized projects as compared to the small-sized ones.

Table 2 presents the estimated effects on project approval rates with additional fixed effects as we move from Column 1-3 (similar to Table 1). Prior to decentralization, mid-sized projects

Table 2—Approval Rates Before and After the Policy

	1(Project Approved)					
	(1)	(2)	(3)	(4)	(5)	(6)
Post	0.05*			0.06**		
	(0.03)			(0.03)		
Middle	0.10*	0.10*	0.09	0.09	0.08	0.07
	(0.06)	(0.05)	(0.06)	(0.05)	(0.05)	(0.07)
Large	0.09	0.09	0.09*	0.11*	0.10*	0.10
	(0.06)	(0.05)	(0.05)	(0.06)	(0.05)	(0.06)
Middle × Post	-0.09**	-0.08**	-0.10*	-0.10**	-0.08*	-0.08
	(0.04)	(0.04)	(0.05)	(0.04)	(0.04)	(0.11)
Large × Post	-0.01	-0.01	-0.01	-0.02	-0.01	0.02
	(0.04)	(0.04)	(0.05)	(0.04)	(0.03)	(0.06)
Mean—Small,Pre	0.67	0.67	0.67	0.67	0.67	0.67
R2	0.11	0.12	0.32	0.12	0.13	0.34
N	3060	3060	2575	2114	2114	1660
State x Cat. FE	Yes	Yes	No	Yes	Yes	No
Year FE	No	Yes	No	No	Yes	No
State x Cat. x Year FE	No	No	Yes	No	No	Yes
Sample	Whole	Whole	Whole	Restricted	Restricted	Restricted

Notes: Data is at the level of project-year. All projects with area 10-100 hectares are in the sample. The time period is 1990-2009. The dependent variable is a dummy that takes value one if the project was approved and is zero otherwise. Middle is a dummy that takes value one if the project area is between 20-40 hectares, and large if it is between 40-100 hectares. Columns (1)-(3) consider the full sample while the last three columns drop projects with area in the range 16-24 hectares and 36-44 hectares. Post is an indicator for years 2004 and after. Column (1) includes state-category fixed effects, while Column (2) adds year fixed effects. Column (3) has state-category-year fixed effects. Standard errors are clustered at the state-category level. *** p<0.01, ** p<0.05, * p<0.1.

were approximately 10 p.p. more likely to be approved as compared to smaller projects. Strikingly, however, after decentralization, the approval probability for these mid-sized projects fell significantly, declining by 8–10 p.p. (12–13%). In other words, when states were now the approving authority, there was no difference in the approval probability between small and medium sized projects, i.e., $\beta_1 + \beta_2 = 0$ (p-val ≥ 0.50 across Columns 1-3), or states were less likely to approve the mid-sized projects they received.

Before we proceed, there are two important caveats in order. First, given the discontinuity in the application density around the policy-relevant threshold, one may be concerned about the endogenous sorting of projects (by altering the size) across the threshold. This would imply that the change in approval probabilities is an artefact of the sorting as opposed to a more general observation throughout the size distribution. To allay this concern, we re-estimate Equation (1) after excluding projects in a 5 Ha. range around the threshold i.e., we exclude projects between $(16, 24)$ Ha. and $(36, 44)$ Ha. As reported in Columns 4-6 of Table 2, the results are quantitatively very similar. We will return to examine this issue more formally in Section 8. Since the probability of approval is a binary variable, we also redo the above analysis using a probit model instead and find consistent results, as reported in Appendix Table A6.

Second, we investigate — and rule out — the possibility that this observed decrease in approval probabilities might simply reflect state governments' capacity constraints or quotas limiting the total number of approvals per year. With higher volume of applications, this would therefore mechanically imply lower approval probabilities. While our qualitative conversations with domain experts does not support this hypothesis, Appendix Figure A2 reports the total number of received and approved applications (as well as area) every year. We see a clear increase in *both* after the policy reform, which suggests that lower approval probabilities were not driven by bureaucratic constraints, but rather reflect differential approval practices by the state and center.

3.3 Interpretation and Implications of Reduced-Form Results

The above empirical observations demonstrate that decentralizing the approval decision from center to states resulted in the latter receiving more applications (Section 3.1), despite having a lower probability of approving these projects on average (Section 3.2). This suggests that either state governments evaluate forest diversion applications differently than the center, or that the application costs are different across them, or both. For example, if applying to the state is less costly compared to the center, then even if the preferences of state and center are similar, it could result in higher volume and worse quality of applications, resulting in lower average probability of approval under the state. In order to empirically estimate the relative application cost and the relative preference weight that the state and center put on economic development vis-a-vis forest conservation, we need to model the applicants' decision to apply, given the approval authority and factors that would impact its decision-making. We discuss this in Section 4 below.

4 Theory

4.1 Model Setup

Governance Structure. There are two types of governments (g) - the central government (c) and a regional government (r) who can take decisions regarding legal deforestation for development projects. Time is discrete and infinite; $t = \{0, 1, 2, \ldots\}$. The economy begins with a stock of forest resource $\mathcal{F}_0$ in period $t = 0$. In each period t, applicants requiring forestland diversion for developmental projects apply for deforestation approvals.

We model a typical region within the country. Note that we can embed this in a larger model of an economy with multiple regions, where each regional government focuses on projects originating in its own region, while the center can approve projects from any region. As we show in the Appendix, in this model with multiple regions, the cental government's approval decision-making becomes additively separable in regions. Any cross-region *externality* in economic value that the center may care more about (but states may not), is incorporated in the

differential welfare weights across governments, as we discuss below. We therefore consider the problem of a typical region instead.

Project Characteristics. In each period, a pool of (potential) applicants are born with development projects. A project is indexed by two characteristics z and S that are exogenously determined: (i) the area of forest land S that needs to be deforested (henceforth, size of the project) and (ii) the project quality $z \sim F_z(z)$ that is observable to the applicant and the approving authority (either the central or regional government), but not to the researcher.[6]

Approval Decision. A project (z, S), if implemented, generates a net economic value $v(z, S) = zq(S)$ where $q(\cdot)$ is strictly increasing and concave in S. Let $c_F(S)$ denote the cost of deforesting the land of size S, where c_F is a strictly increasing and weakly convex function of S. The approving authority (either the central or regional government), upon receiving an application for project (z, S) must decide whether to approve it or not. In addition to the economic benefit and cost of the project, the government has a project-specific idiosyncratic taste (or, preference) shock $\eta \sim F_\eta(\eta)$. This creates uncertainty about the outcome of the application at the time of seeking approval. Lastly, the government places an (endogenously chosen) weight b_{gt} on evaluating the net benefit from approving projects. In other words, b_{gt} captures the 'development-conservation' tradeoff faced by the approving authority. For example, if the projects generate large positive externalities for the economy, then b_{gt} would be higher. If, on the other hand, the forest loss due to the projects' approvals generate large negative externalities, or have significant adverse impact on future payoff (due to lower stock of forests), then b_{gt} would be lower. Given the above, an approving authority g approves the project if the benefits exceed the costs (as we will formalize in Section 4.2 below).

Application Decision. An applicant with project (z, S) has to decide whether to apply for the project or not. Applicants get payoff zero if they don't apply or their application is not approved.[7] Applying for forestland diversion is also costly for the applicant. We assume that the cost of application for a project of size S to government g is $\lambda_g c_A(S)$. $c_A(S)$ is strictly increasing and weakly convex function of project size S. λ_g is a cost-shifter that captures (in a reduced-form way) differential application costs that an applicant faces for applying to a government g. Our qualitative conversations with domain experts suggest that the application cost is largely related to procedural activities (e.g., paperwork, bureaucratic requirements, etc.), it depends on the project size (since larger areas have more requirements and lengthier procedures), but not on the quality of the project per se. That said, we allow for the application cost to be dependent on the approving authority (as captured by λ_g) to capture local bureaucratic connections and networks that might reduce the "effective cost" of an application .

[6] We observe a proxy of project quality for years after 2014 in the data. We use it to validate the model predictions on project quality as discussed in Section 6.2.

[7] Applicants are assumed to live for just one period. Making the applicant long-lived will introduce the possibility of strategic timing of the application. This will substantially increase the complexity of the model without adding much insight beyond what the current model already delivers.

Timeline Within Each Period: The application and decision-making process timeline within each period t is as follows:

Step 1. At the beginning of every period t, the approving authority g *chooses* a parameter b_{gt}, which captures the 'development-conservation' tradeoff.

Step 2. Applicants with projects (z, S) observe b_{gt} and decide *whether* to apply, given application cost $\lambda_g c_A(S)$.

Step 3. The approving authority realizes project-specific taste shocks $\eta \sim F_\eta$ and decides on the approval decision for all the applied projects.

4.2 Approval Decision

We solve this model using backward induction, starting with the decision to approve projects (Step 3). For a time period t, an approving authority (g) approves a project (z, S) if the net benefits are greater than the costs. This implies:

$$b_{gt} z q(S) \geq \eta c_F(S)$$

This implies an ex-ante approval probability given by:

$$P_{gt}(z, S) \;=\; F_\eta \Big[b_{gt} z \phi(S) \Big] \tag{2}$$

where $\phi(x) = \frac{q(x)}{c_F(x)}$ is the benefit-cost ratio for a project of size S. Given the assumptions on $q(x)$ and $c_F(x)$, note that $\phi'(x) < 0$.

Lemma 1 *Conditional on size, higher quality projects are more likely to be approved, i.e., $\partial P_{gt}/\partial z > 0$. Moreover, conditional on the quality of the project, larger projects are less likely to be approved, i.e., $\partial P_{gt}/\partial S < 0$.*

See Appendix B.1 for the proof. Intuitively, conditional on S, higher z increases the benefits of the project, thus increasing the probability that it is approved. On the other hand, conditional on a project of quality z, larger projects have (weakly) decreasing marginal benefits, but (weakly) increasing marginal costs, thus reducing the probability that they are approved.

4.3 Application Decision

Given the expected probability of approval (Equation 2), the applicant's expected payoff from applying to g, denoted by $u_g(z, S)$, can be given by:

$$u_{gt}(z, S) \;=\; P_{gt}(z, S) v(z, S) - \; \lambda_g c_A(S) \tag{3}$$

where the first term in the above expression captures the expected benefits, while the latter is the application cost. An applicant will therefore submit the project as long as $u_{gt}(z, S) \geq 0$. Since $\partial u_{gt}(z, S)/\partial z > 0$, it implies that for a given S, there is a threshold level of quality $z^*_{gt}(S)$ such that the applicant will apply only if $z \geq z^*_{gt}(S)$, where $z^*_{gt}(S)$ is given implictly by:

$$P_{gt}\left[z^*_{gt}, S\right] \times z^*_{gt}\phi_A(S) = \lambda_g \tag{4}$$

where: $\phi_A(x) = \frac{q(x)}{c_A(x)}$ is the benefit-cost ratio for the applicant. Similar to $\phi(x)$, $\phi'_A(x) < 0$.

Lemma 2 *The threshold quality (z^*_{gt}) is increasing in the size of the project, i.e., $\partial z^*_{gt}/\partial S > 0$.*

See Appendix B.2 for the proof. Intuitively, since larger projects (higher S) have a lower probability of being approved and higher application costs, they have to be of higher quality (z) to be applied. Put together, the mass of *applied* projects of size S, denoted by the PDF $\xi_{gt}(S)$, will be the set of projects for $z \geq z^*_{gt}$ so that:

$$\xi_{gt}(S) \;=\; \bar{\xi}_g(1 - F_z(z^*_{gt}(S))) \tag{5}$$

where $\bar{\xi}_g$ is a normalization constant defined to ensure the validity of the density function $\xi_{gt}(S)$. Note that Lemma 2 implies that the density function should fall with project size. This is consistent with the empirical density of applications reported in Figure 2a earlier. Lastly, the average approval probability for all applied projects of a given size S is therefore given by:

$$\overline{P}_{gt}(S) \equiv E(P_{gt}(z)|S) = \int_{z \geq z^*_{gt}(S)} P_{gt}(z, S)\frac{dF_z(z)}{1 - F_z(z^*_{gt}(S))} \tag{6}$$

Again, note from Lemma 2 that *conditional on applying*, larger projects are (on average) of a higher quality, which from Lemma 1, further implies a higher expected probability of approval. In other words, the probability of approval *conditional on an application* should be increasing in project size, which is again consistent with the empirical pattern in Figure 2a.

4.4 Government's Long-run Payoff

We finally examine the choice of b_{gt} from Step 1 in the timeline. Define the lifetime payoff of a government g as:

$$\Pi_g(R_0) = \omega_g \underbrace{\left[\sum_{t=0}^{\infty} \beta^t V_{gt}\right]}_{\text{P.V. of Economic Benefits}} + \underbrace{\left[\sum_{t=0}^{\infty} \beta^t c_0(\mathcal{F}_{gt} - D_{gt})\right]}_{\text{P.V. of Forest Conservation}} = \sum_{t=0}^{\infty} \beta^t \left\{\omega_g V_{gt} + c_0(\mathcal{F}_{gt} - D_{gt})\right\} \tag{7}$$

where ω_g represents the fundamental, long-term welfare weight that a government g places on economic development (relative to forest conservation). β is the discount factor and V_{gt} is the

aggregate value generated from all the projects approved by government g in period t. Let $\mathcal{F}_{gt}$ be the stock of forest at the beginning of period t and D_{gt} be the total deforested area in period t. Hence, $c_0(\mathcal{F}_{gt} - D_{gt})$ is the flow payoff from remaining stock of forest at the end of period t. For any choice of b_{gt} in period t, D_{gt} is given by:

$$D_{gt} = \int_S \int_{z \geq z^*_{gt}(S)} S \cdot P_{gt}(z, S, b_{gt}) dF_z(z) dG_{\mathcal{F}}(S) \tag{8}$$

where $z^*_{gt}(S)$ is the (dynamic) threshold quality for applications (as defined in Equation 4) and $G_{\mathcal{F}}(\cdot)$ is the size distribution of all potential projects that can be applied, given the stock of forest $\mathcal{F}$. Similarly, V_{gt} can be given by:

$$V_{gt} = \int_S \int_{z \geq z^*_{gt}(S)} z q(S) P_{gt}(z, S, b_{gt}) dF_z(z) dG_{\mathcal{F}_{gt}}(S) \tag{9}$$

The optimization problem for the government g is therefore to choose the "short-term" preference parameter b_{gt} to maximize its lifetime payoff:

$$\begin{aligned} \max_{\{b_{gt}\}} \Pi_g(\mathcal{F}_0) = \quad & \max_{\{b_{gt}\}} \quad \sum_{t=0}^{\infty} \beta^t \left\{ \omega_g V_{gt} + c_0(\mathcal{F}_{gt} - D_{gt}) \right\} \\ \text{s.t.} \quad \mathcal{F}_{t+1} = \quad & \mathcal{F}_t - D_t \quad \text{and Equations (8) and (9)} \end{aligned} \tag{10}$$

While there is no closed-form solution for this general case, we will be able to derive one after parameterizing the underlying project quality (z) and η distributions, as described in Section 5 below.

5 Model Identification and Calibration

5.1 Parameterization

Distributional Assumptions. We make the following distributional assumptions: (i) the distribution of project quality follows a Pareto distribution with a shape parameter θ i.e., $z \sim Pareto(\theta)$, where $F_z(z) = 1 - z^{-\theta}$; (ii) η follows a uniform distribution on $[0, 1]$, where $F_\eta(\eta) = \eta$.[8]

Lemma 3 *Assume $\eta_t \sim Uniform(0, 1)$ and $z \sim Pareto(\theta)$. Then the probability of approval, the threshold quality of application, along with the density of applied projects and their average approval*

[8]Restriction to the range $[0, 1]$ is without loss of generality. If η is distributed uniformly over $[0, K]$, we can rewrite $\eta c_G(S)$ as $\eta^{'} c^{'}_G(S)$ where $c^{'}_G(S) = K c_G(S)$ and $\eta^{'} = \eta / K$ is uniform over $[0, 1]$.

probability (from Section 4) can be expressed as:

$$P_{gt}(z,S) = b_{gt} z \phi(S) \qquad \textit{(Probability of approval, Eq. 2)}$$

$$z^*_{gt}(S) = \sqrt{\frac{\lambda_g}{b_{gt}\phi(S)\phi_A(S)}} \qquad \textit{(Threshold quality, Eq. 4)}$$

$$\xi_{gt}(S) = \bar{\xi}_g (z^*_{gt})^{-\theta} \qquad \textit{(Density of Applied Projects, Eq. 5)}$$

$$\overline{P}_{gt}(S) = \frac{\theta}{\theta - 1} \times \underbrace{b_{gt} z^*_{gt} \phi(S)}_{=P_{gt}(z^*_g, S)} \qquad \textit{(Avg. Approval Prob., Eq. 6)}$$

$$V(P_{gt}(S)) = \frac{2}{\theta - 2} \overline{P}^2_{gt} \qquad \textit{(Variance in Approval Prob.)}$$

Appendix Section B.3 provides the proof. The above distributional assumptions also enable us to derive closed-form solutions for the dynamic evolution of the short-term preference parameter for development (relative to conservation) b^*_{gt} that we show in Lemma 4 below.

Lemma 4 *Assume $\eta_t \sim$ Uniform$(0,1)$ and $z \sim Pareto(\theta)$. For any parameter x_g, let x be their ratio between the regional and central government i.e., define $x = x_r/x_c$. This implies that the optimal choice of b^*_{gt} as well as its ratio between regional and central government can be expressed as:*

$$b^*_{gt} = \omega_g^2 \lambda_g \kappa(\mathcal{F}_t) \quad \textit{where } \kappa(\mathcal{F}_t) = \left[\frac{\theta}{\theta+1}\frac{1-\beta}{c_0}\frac{\Gamma_V(\mathcal{F}_t)}{\Gamma_D(\mathcal{F}_t)}\right]^2 \tag{11}$$

$$b^* = \omega^2 \lambda \tag{12}$$

See Appendix Section B.4 for proof. The evolution of b^*_{gt} therefore stems from two distinct sources.

First, the available stock of forests $\mathcal{F}_t$ that operates through the $\kappa(\mathcal{F}_t)$ function. Intuitively, Γ_V and Γ_D capture the relative marginal benefit to cost of deforestation. Conditional on the stock of forests ($\mathcal{F}_t$), a higher cost of deforestation (c_0) decreases b^*_{gt} because governments put a lower weight on the value of any given project during the approval process. Similarly, a more patient government (i.e., higher β) chooses a lower b^*_{gt}, as the stock of forest has higher continuation payoff.

Second, b^*_{gt} depends on the two fundamental parameters ω_g and λ_g. In particular, ω_g captures the long-term weight on development vis-a-vis conservation. Therefore, a higher ω_g also implies a higher (short-term) weight b_{gt}. Similarly, λ_g reflects the application costs. A higher application cost would imply a better selection of projects that apply (higher z^*), which in turn (ceterus paribus) makes a government more likely to approve them (higher b_{gt}).

Lastly, our structure allows us to retrieve a tractable mapping to understand *differences* in approval rates across governments. In particular, the ratio of b^*_{gt} across governments (for the same endowment of forests), will purely reflect differences in the underlying fundamentals. In other words, $b^* = b^*_{rt}/b^*_{ct}$ is *constant* and given by $\omega^2 \cdot \lambda$, where $\omega = \omega_r/\omega_c$ and $\lambda = \lambda_r/\lambda_c$.

5.2 Identification

With the above parameterization, we now turn to identifying these parameters from the data. A key advantage of our setting is that we can observe the entire universe of applications made, along with their approval outcomes. As is evident from Lemma 3, *both* are required to identify the fundamental parameters related to government's preferences (ω_g) and applicant costs (λ_g).

In the ideal case, observing the distribution of applications and approvals *separately* for *both* the center and state across the entire size distribution would enable us to identify $\{\omega_g, \lambda_g\}$ separately for each government. However, this is clearly not possible in our context since the approving authority (state vs central governments) simultaneously operate on specific domains of the size distribution.

Nonetheless, the decentralization policy reform (discussed earlier in Section 2.2) provides us with a unique way to identify the *relative* ratios of these two parameters between the state and center i.e., help identify $\{\omega, \lambda\}$. Specifically, since approval for mid-sized projects in the interval $S \in [20, 40]$ were decentralized from the center to the state, we can use this policy reform, along with the *change* in the density and approvals of applications to identify the relative parameters $\{\omega, \lambda\}$. We elaborate on this identification below.

Note that simply using the change in the application density and approvals for mid-sized projects is insufficient for identification because the decentralization 'treatment' is confounded by temporal changes in these moments over time. For example, from Lemma 3, note that a change in the approval probability (P_{gt}) for mid-sized projects before and after the policy reform could stem from either a shift in the approving authority from center to state, or simply because the relative production and cost functions of a project ($\phi(S)$) has changed over time.

To make progress, we assume that for a government g: $\phi_{gt}(S) = (\alpha_g)^t \phi_0(S)$ and $\phi_{Agt}(S) = (\beta_g)^t \phi_{A0}(S)$, for some constants α_g and β_g. In other words, we allow for a government-specific evolution [9] We now take advantage of the policy reform, which was only applicable to mid-sized projects, $S \in [20, 40]$, denoted by MID.[10] We refer to the projects with size $S \in (10, 20)$ as SMALL.

[9] Note that in theory, *both* the initial level of $\{\phi_0(S), \phi_{A0}(S)\}$ as well as their rate of change over time $\{\alpha_g, \beta_g\}$ can vary across center and state governments. However, we do not have any empirical variation to identify these separately because the institutional context perfectly separates the approval decisions by the two governments across the size distribution. Therefore, we assume that they are the same in the pre-policy period, but allow them to change at different rates.

[10] To eliminate endogenous sorting across the thresholds (that we will come back to later in Section 8), we consider the interval $S \in [25, 35]$, which we refer to as MID sized; and projects with $S \in [10, 15]$ as SMALL sized.

5.2.1 Identification of ω

Suppose that the policy reform happened in period $t = 1$. Then comparing period 0 (pre-policy period) and any $t > 0$ (post-policy period) we get from Equation (**??**):

$$\left[\frac{z^*_{c0}}{z^*_{rt}}\right]^{\text{MID}} = \sqrt{\frac{b^*}{\lambda}} \times \sqrt{\frac{\phi_{rt}\phi_{Art}}{\phi_{c0}\phi_{Ac0}}} = \underbrace{\sqrt{\frac{b^*}{\lambda}}}_{=\omega} \times \underbrace{\sqrt{(\alpha_r\beta_r)^t}}_{\text{= Time Trend}} \tag{13}$$

$$\left[\frac{z^*_{rt}}{z^*_{r0}}\right]^{\text{SMALL}} = \sqrt{\frac{\phi_{r0}\phi_{Ar0}}{\phi_{rt}\phi_{Art}}} = \sqrt{\frac{1}{(\alpha_r\beta_r)^t}} \tag{14}$$

Identifying ratio of z^*_g: We do not observe z^*_g in the data. To identify the ratio of z^*_g we write down the PDFs of S for the pre- and post-policy periods, denoted by $\xi_0(S)$ and $\xi_t(S)$, respectively, which we do observe in the data. Specifically from Equations (**??**) and (**??**), the density in the pre-reform period will be given by:

$$\xi_0(S) = \bar{\xi}_0 z^*_{g0}(S)^{-\theta}$$

where $g = r$ if $S \in [10, 20)$ and $g = c$ if $S \in [20, 100]$. Similarly, in the post-reform period:

$$\xi_t(S) = \bar{\xi}_t z^*_{gt}(S)^{-\theta}$$

where $g = r$ if $S \in [10, 40]$ and $g = c$ if $S \in (40, 100]$. $\bar{\xi}_0$ and $\bar{\xi}_t$ are appropriately defined positive constants that make ξ_0 and ξ_t valid PDFs. We compute:

$$\chi_0 \equiv \underbrace{\left\{\frac{\xi_0^{\text{MID}}}{\xi_0^{\text{SMALL}}}\right\}^{-\frac{1}{\theta}}}_{\text{Data}} = \frac{z^{*\,\text{MID}}_{c0}}{z^{*\,\text{SMALL}}_{r0}} \quad \text{and} \quad \chi_t \equiv \underbrace{\left\{\frac{\xi_t^{\text{MID}}}{\xi_t^{\text{SMALL}}}\right\}^{-\frac{1}{\theta}}}_{\text{Data}} = \frac{z^{*\,\text{MID}}_{rt}}{z^{*\,\text{SMALL}}_{rt}} \tag{15}$$

which gives us:

$$\underbrace{\frac{\chi_0}{\chi_t}}_{\text{Data}} = \left[\frac{z^*_{c0}}{z^*_{rt}}\right]^{\text{MID}} \times \left[\frac{z^*_{rt}}{z^*_{r0}}\right]^{\text{SMALL}} = \sqrt{\frac{b^*}{\lambda}} = \omega \tag{16}$$

5.2.2 Identification of b^* and λ

Equation (**??**) shows that the period-specific preference parameter (b^*) depends on both ω and λ. Therefore, without understanding how application costs differ across the center and the state (which is what λ captures), knowing only ω will not help us understand how center and state governments approve projects. For example, if it is less costly to apply to states than center (i.e., $\lambda < 1$), then the state will approve projects more stringently than the center (i.e., $b^* < 1$), even if their welfare weights were identical (i.e., if $\omega = 1$). Therefore, we need to identify λ. Moreover, we need identification of b^* as well, since it can help us validate Equation

(**??**) by examining subsamples. To identify b^* and λ, we utilize the other observable outcome - the average approval probability as a function of S, along with the PDF of S. From Equation (**??**) we get

$$\underbrace{\left[\frac{\overline{P}_t}{\overline{P}_0}\right]^{\text{MID}}}_{\text{Data}} = \frac{\overline{P}_{rt}}{\overline{P}_{c0}} = \frac{b^*_{rt}}{b^*_{c0}} \times \frac{z^*_{rt}}{z^*_{c0}} \times \frac{\phi_{rt}}{\phi_{c0}} = \underbrace{\sqrt{\frac{b^*_{rt}}{b^*_{c0}}\lambda}}_{\text{= Policy Impact}} \times \underbrace{\sqrt{\left(\frac{\alpha_r}{\beta_r}\right)^t}}_{\text{= Time Trend}} \tag{17}$$

$$\underbrace{\left[\frac{\overline{P}_t}{\overline{P}_0}\right]^{\text{SMALL}}}_{\text{Data}} = \frac{\overline{P}_{rt}}{\overline{P}_{r0}} = \frac{z^*_{rt}}{z^*_{r0}} \times \frac{\phi_{rt}}{\phi_{r0}} = \sqrt{\frac{b^*_{r0}}{b^*_{rt}}} \times \sqrt{\left(\frac{\alpha_r}{\beta_r}\right)^t} \tag{18}$$

The LHS of Equations (17) and (18) are observable. Let's denote $\mathcal{P}^X = \left[\frac{\overline{P}_t}{\overline{P}_0}\right]^X$ for $X =$ SMALL, MID. Using Equations (16), (18) and (17), we get:

$$\underbrace{\frac{\chi_0}{\chi_t}}_{\text{Data}} = \sqrt{\frac{b^*}{\lambda}} \qquad \text{and} \qquad \underbrace{\frac{\mathcal{P}^{\text{MID}}}{\mathcal{P}^{\text{SMALL}}}}_{\text{Data}} = \sqrt{\lambda \times \frac{b^*_{rt}}{b^*_{c0}}} \times \sqrt{\frac{b^*_{r0}}{b^*_{rt}}} = \sqrt{b^*\lambda} \tag{19}$$

$$\Rightarrow b^* = \frac{\mathcal{P}^{\text{MID}}}{\mathcal{P}^{\text{SMALL}}} \times \frac{\chi_0}{\chi_t} \qquad \text{and} \qquad \lambda = \frac{\mathcal{P}^{\text{MID}}}{\mathcal{P}^{\text{SMALL}}} \times \frac{\chi_t}{\chi_0} \tag{20}$$

Note that for now, we do not allow any possibility for an applicant to manipulate the project size (especially around the threshold) to endogenously choose the approving authority. While such sorting concerns may be valid for projects near the policy threshold, the *selection* of projects with a change in the approving authority is more likely to be a general feature. We therefore abstract away from it in our baseline model. However, in Section 8, we do augment our baseline model to allow for endogenous sorting around the threshold. Our calibration exercise indicates that sorting can explain only around 13% of the change in the density of applications that we empirically observe around the policy threshold.

5.3 Estimation Results

Having established how our theoretical model maps clearly to empirical moments observed in our data (Equations (**??**)-(11)), we now proceed to estimate the four key parameters of interest: (i) the shape parameter for the distribution of project quality (θ); (ii) the relative welfare weight placed by state governments compared to the central government on economic development (ω); (iii) the relative application cost faced by applicants when applying to state governments compared to the central government (λ); and (iv) the period specific preference parameter used by state government vis-a-vis the center on economic development (b^*). We proceed as follows:

Step 1. We first pool all projects from both the pre-reform and post-reform periods (1990-2009). For each project size (S), discretized into increments of 1 Ha. for precision, we calculate three empirical moments from our data: (i) the density of applications; (ii) the average approval probability; (iii) and the variance of approval probabilities.

Table 3—Estimates of θ, b, λ

	Estimate	S.E.
θ	7.28	0.45
b	0.89	0.07
λ	0.85	0.07
$\sqrt{\lambda/b}$	0.98	0.02
$\sqrt{b\lambda}$	0.87	0.07

Notes: The above table reports the parameter estimates. We exclude those applications between 15-25 Ha. Appendix Table A3 shows the results across alterante sample specifications.

Step 2. We re-arrange Equation (11), $\hat{\theta} = 2(1 + \overline{P}_g^2/V(P_g))$. Since we observe approval probabilities and their variance in the data for each project size S, this procedure generates an estimate $\hat{\theta}$ for each size. Our preferred value of θ is the median of these estimates across all sizes, providing a robust central measure.

Step 3. Next, we use the empirical application densities ($\xi(S)$) and the estimated shape parameter $\hat{\theta}$ to calculate the size-specific quality threshold $(\xi(S))^{-1/\hat{\theta}}$, reflecting the minimum project quality required for applicants to propose their projects to the government.

Step 4. Given the computed threshold qualities and empirical approval probabilities from pre- and post-reform periods, we calculate average values for two size intervals of interest: small- and mid-sized projects. We then compute two key empirical ratios: (i) the ratio of the density of mid-sized to small-sized projects (χ_1/χ_0) across periods; and (ii) the ratio of their respective average approval probabilities (P^{MID}/P^{SMALL}). Substituting these empirical ratios into our identification equations (Equation 20), we obtain direct estimates of b and λ.

Step 5. We bootstrap the sample 500 times using state-year as clusters and generate the standard errors of the estimates.

Calibrated values: Table 3 reports the results. The estimate of θ is 7.28. The relative preference weight (b) placed by state governments on economic development (relative to conservation), compared to the central government, is estimated to be 0.89. This implies that state governments place an approximately 11% lower weight on the economic benefits of forest-diversion projects compared to the central government, reflecting a stronger preference for

forest conservation. The relative application cost (λ) faced by applicants under state governments, compared to the central government, is 0.85, indicating 15% lower costs (or frictions) when applying for forestland diversion approvals from state governments relative to the central government.

Interpretation: Interpreting these parameters through our theoretical lens highlights two critical channels through which decentralization affects project applications and approvals: (i) reduced approval probability due to higher conservation preference (Lower b) — state governments' lower preference weight ($b = 0.89$) implies that decentralization directly promotes greater forest conservation by making approvals more stringent; and (ii) increased application volume due to lower application cost (lower λ) — the estimated reduction in application cost ($\lambda = 0.85$) significantly lowers applicants' barriers to submitting proposals to state governments. Consequently, this encourages more — potentially lower quality — projects to apply. Quantitatively, this implies an 18% increase in the number of mid-sized applications ($(\sqrt{\lambda/b})^{-\theta} = 1.18$) following decentralization, offsetting some of the direct conservation benefits derived from the states' more stringent approval standards.

These two channels jointly determine the overall impact of decentralization on aggregate deforestation and economic outcomes. Combining our parameter estimates ($\sqrt{b\lambda} = 0.87$), we find that decentralization leads to a net reduction in average approval probability of approximately 13%, which, when coupled with an 18% increase in application volume, implies a modest net increase of about 3% in aggregate deforestation. This result emphasizes that although decentralization fosters stricter approvals by states, the concurrent surge in project applications due to reduced application costs substantially attenuates these conservation gains.

Robustness Across Samples: Our preferred estimates excludes the sample between 15-25 Ha. to account for endogenous sorting across the threshold. However, Appendix Table A3 shows that the parameter estimates of b and λ are robust to alternate sampling restrictions, specifically: (i) across time — pooling the pre- and post-policy reform periods, as opposed to considering them separately; (ii) across size — considering with ("Whole Sample") and without ("Restricted Sample") the projects with size in the neighborhood of the policy thresholds (15-25 Ha.). The values for b and λ remain remarkably stable and consistent across different sample definitions and restrictions, ranging narrowly around their preferred values of 0.89 (for b) and 0.85 (for λ). The shape parameter (θ) shows slightly more variation, ranging from 6.29 to 8.34 across specifications, but without altering our qualitative conclusions.

6 Model Validation

In this section, we undertake several validation exercises to build confidence in the structural estimates derived above and to demonstrate the consistency and robustness of our findings.

Specifically, we present four validation tests that reinforce the credibility of our parameter estimates and illustrate the real-world empirical relevance of our theoretical framework.

6.1 Validation from the Reduced Form Result

We begin by comparing our model-based estimates to the reduced-form results presented earlier in Section 3. Recall that our structural estimation (Section 5.2) implies that decentralization reduces the average approval probability for mid-sized projects (from Equation (19)) by approximately 13%, captured by the estimate $\sqrt{b^*\lambda} = 0.87$.

We now compare this model-based estimate directly with our difference-in-differences regression estimates from Table 2. We can calculate $\sqrt{b^*\lambda} - 1$ as $\hat{\beta}_2/E(P_{i0}|\text{Mid, Before 2004})$. Substituting in the values from Column 3, this is equal to -0.08/0.77 = -0.10. In general across Columns 1-6, this value varies from -0.10 to -0.13, which implies a $\sqrt{b^*\lambda}$ ranging from of 0.87-0.90, in line with our estimate from Table 3.

6.2 Quality of Projects Received Across Governments

A key insight from our model is that decentralization increases the volume of project applications to state governments, but simultaneously reduces the average quality of these applications. While we clearly document the receipt of more applications in Figure 3, we do not have a direct measure for project quality in the main sample. We therefore use a supplementary project-level application data from 2014 onwards. Applications for each project after 2014 asked applicants to provide details of the employment that would be generated from a project if it were to be approved.

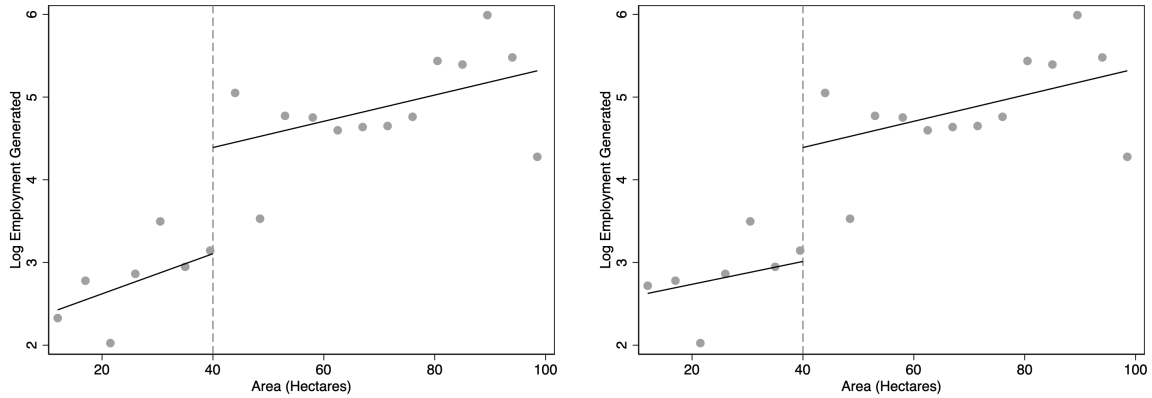
Specifically, for each project size (measured in Ha.), we calculate the minimum (log) employment reported by applicants during 2014–2019. Within our model framework, this minimum employment measure serves as an empirical proxy for the minimum quality threshold required for application ($z_g^*(S)$).[11] As a check for consistency, we show that the density of applications received in the 2014-19 period (Figure A5) also exhibit the same discontinuity that we observe in the 2004-09 period (Figure 3). In particular, we do not find any discontinuity at 20 Ha. (Figure A5a) and a substantial discontinuity in the density of applications around the 40 Ha. threshold (Figure A5b).

Our model predicts two clear patterns: first, the minimum quality threshold ($z_g^*(S)$) is increasing in project size; second, because application costs and approval preferences differ across governments, state governments attract applications of relatively lower quality compared to the center. Hence, we expect to find a discontinuous jump in the minimum employment generated at the policy threshold of 40 Ha., when the approving authority switches from the state to center.

[11] We discretize the size into bins of 1 Ha.

Figure 5—Project Quality Around the Policy Thresholds

(a) Minimum Employment Generated **(b)** 1st Percentile of Employment Generated



Notes: The above figures plot the area of the proposed project (in hectares) on the horizontal axis, and the log of total employment generated by the project on the vertical axis. All projects proposed between 2014-2021 with area between 10-100 Ha. are in the sample. Figure (a) plots the minimum of the log-employment generated by the project, while Figure (b) plots the 1st percentile of the log-employment generated.

We test this hypothesis by plotting the minimum log employment reported for a size S around the size threshold of 40 Ha. As reported in Figure 5a, we find that the minimum (log) employment generated exhibits positive discontinuity at the threshold of 40 Ha. It is also lower on average for projects received by the state (as compared to the center). This pattern is robust even if we define this measure using the 1st percentile as compared to the minimum (Figure 5b). Appendix Table A10 formalizes this and reports the regression discontinuity coefficients for the minimum employment (Column 1) as well as its 1st and 2nd percentiles (Columns 2-4). All coefficients are positive in magnitude and statistically significant at conventional levels.

These empirical findings validate our model's core prediction — that decentralization leads state governments to attract projects of lower quality, consistent with our structural estimates of reduced application costs and altered preferences.

6.3 Heterogeneity in Parameter Estimates

Lastly, our baseline structural estimates (ω, b^* and λ) implicitly assume homogeneous preferences and application costs across states and districts. However, such parameters could realistically vary depending on local institutional characteristics and resource availability. We now explicitly explore such heterogeneity by examining whether state-level corruption and district-level forest cover influence the relative welfare weights (ω) and application costs (λ) across jurisdictions.

Specifically, we examine three distinct sources of heterogeneity – administrative, environmental and political. First, applicants dealing with a more corrupt bureaucracy may face significantly lower effective application costs, as corruption often expedites bureaucratic processes through informal channels. Therefore, we expect λ to be lower in more corrupt states as compared to lesser corrupt ones. However, we do not expect bureaucratic corruption to affect

state's welfare weight ω. Hence, our model predicts b^* to be lower in more corrupt states. Second, state governments with higher baseline forest cover may place greater welfare weight on forest conservation, either due to stronger citizen preferences for conservation (as suggested in Appendix Table A9), or greater state revenues from forest resources, thus implying lower ω in those regions. However, we do not anticipate λ to be correlated with baseline forest cover. Therefore, we hypothesize that b^* would be lower in states with higher forest cover. Finally, if the state and central governments are political aligned, i.e., if they are ruled by the same political party or coalition, then the application cost would be similar across the two levels, resulting in lower λ. This could be because information flow between the two levels would be smoother, resulting in faster processing of the application at the center.

To test these hypotheses, we compile three datasets. First, we access the 2005 Transparency International report about corruption in different states of India. The report provides indices of corruption in various state agencies, such as lower judiciary, police, public hospital, schools etc., for about 20 states. We focus on the corruption index of municipalities, which measure corruption at the district level, the level at which the applicants first apply for approval for forestland diversion. We divide our data into projects located in states with higher and lower than the median index. Secondly, we estimate state level forest cover using the Vegetation Continuous Fields data (obtained through the SHRUG database) that measures tree cover at 250m resolution. We create a district-year level panel data from 2000 to 2019 on percentage of land area under forest cover (Dimiceli et al. 2015, Asher et al. 2021).[12] We then compute the state level forest cover and partition the sample of projects into those located in states which had an above- and below-median forest cover in the year 2000 – the first year for which we have forest cover data. Finally, we compile a dataset of ruling coalitions at the state and center from 1990-2009, which allows us to measure for each state-year, whether the state and center were politically aligned. We calculate the average value of the alignment status for each state (over the period of study), and partition the states into above and below median of average alignment.

Table 4—Estimation of b^*, λ and ω in sub-samples

	Below Median			Above Median		
	(1)	(2)	(3)	(4)	(5)	(6)
	b^*	λ	ω	b^*	λ	ω
Municipality Corruption	1.12	1	1.06	0.94	0.8	1.08
	(0.87, 1.37)	(0.76, 1.24)	(0.97, 1.15)	(0.75, 1.13)	(0.65, 0.96)	(1.02, 1.15)
Baseline Forest Cover	1.19	1.05	1.06	0.87	0.97	0.95
	(0.99, 1.39)	(0.87, 1.23)	(1.01, 1.12)	(0.69, 1.05)	(0.81, 1.13)	(0.87, 1.02)
Political Alignment	0.85	0.79	1.04	1.02	1.02	1.00
	(0.69, 1.01)	(0.66, 0.92)	(0.98, 1.10)	(0.79, 1.26)	(0.80, 1.24)	(0.93, 1.07)

Notes: The above table provides estimates for b^*, λ and ω separately in Columns (1)-(2) and (3)-(4) for: (i) districts with below- and above-median forest cover in the year 2000 (first year in our data); (ii) states without and with a regional office present; and (iii) states without and with a politically aligned government with the center in the year of projects' application.

Table 4 reports the estimates of b^*, λ and ω in the below- and above-median samples for each

[12]VCF is predicted from a machine learning algorithm based on broad spectrum satellite images and trained with human-categorized data, which can distinguish between crops, plantations and primary forest cover.

of the three measures – municipal corruption index, baseline forest cover and average political alignment. Consistent with the hypothesis above, we find that for states with higher than median corruption index, the estimate of λ is 0.8 and is statistically significantly lower than 1. On the other hand, in states with below-median corruption, λ estimate is 1, i.e., for those states the application costs are same across the two tiers. The estimates of ω for the two samples are 1.06 and 1.08; they are not statistically different from each other. However, the estimate for b^* is 0.94 for more corrupt states, but is 1.12 for less corrupt ones. Therefore, we find that more corrupt states behave as if they are more pro-conservation than the center, even though their fundamental preference is more favorable to development.

The opposite is true when we examine variation by baseline forest cover. For states with above-median baseline forest cover, $\omega = 0.95$, while the estimate is 1.06 for states with lower baseline forest cover. Their estimates of λ are not statistically different from each other. This indicates that greater baseline forest resources increase states' preference toward conservation, without substantially affecting application costs. Consequently, we find the estimate of b^* to be statistically lower for states with higher forest cover.

Finally, states that are more politically aligned on average have an estimated λ not statistically distinguishable from one, indicating similar application costs across tiers. For states that are less politically aligned, the estimate of λ is 0.79, statistically lower than one, indicating higher application cost at the center relative to the state, as hypothesized. The estimates of ω across the two samples are not statistically different. As as result, we find politically mis-aligned states have a statistically lower b^* than more aligned states, making them behave more pro-conservation than what their fundamental preference would reflect.

Together, these heterogeneous parameter estimates highlight important state specific factors shaping the decentralization outcomes, emphasizing that the aggregate impact of decentralization on deforestation and economic development may crucially depend on local institutional and political characteristics and resource endowments.

6.4 Time Taken for Approval Decision

An additional prediction from our model is that decentralization, by increasing the number and lowering the quality of applications received by state governments, should also increase the bureaucratic time taken for approval decisions. We directly test this implication using data on the duration (in days) between the date of application submission and the date of project approval. We separately examine two distinct stages of approval recorded in our dataset: Stage 1 (initial assessment) and Stage 2 (final approval).

We calculate the number of days between the application date and the decision dates for Stages 1 and 2 and re-estimate Equation (1). The results are reported in Tables A7 and A8 for Stage 1 and Stage 2 respectively. The results clearly demonstrate that, following decentralization, the average time taken to approve mid-sized projects (20–40 Ha.) increased substan-

tially. Specifically, Stage 1 approvals took approximately 90–120 days (15–20%) longer post-decentralization, and Stage 2 approvals similarly increased by around 130–180 days (13–17%). These statistically robust findings align precisely with our model's mechanism: state governments, facing increased volumes of lower-quality applications, require significantly longer to reach approval decisions.

7 Aggregate Effects of Decentralization

In this section, we examine the aggregate effects of decentralization on deforestation and economic development. Specifically, we investigate how decentralization has affected deforestation and broader economic outcomes at the district level. We first empirically measure these aggregate effects, and then use our calibrated model to provide a deeper theoretical rationale for these observed impacts.

7.1 Empirical Measurement

To empirically measure the aggregate effects of decentralization, we construct a district-level panel dataset containing annual measures of forest cover and economic development. Our measure of forest cover is obtained from satellite-based Vegetation Continuous Fields (VCF) data, providing precise district-level estimates of forested land area from 2000 to 2009. For economic development, we use annual nightlight luminosity data, available from 1994 to 2009, which is a common proxy for economic activity and growth (Asher et al. 2020).

We exploit variation in district-level exposure to decentralization by measuring the fraction of mid-sized projects (20–40 Ha.) that a district had prior to the 2004 policy reform. Therefore, districts with a larger fraction of mid-sized projects before 2004 experienced greater decentralization, as their approval authority shifted from the central government to state governments. We estimate the following regression:

$$Y_{dt} = \alpha_d + \alpha_t + \beta_M \text{Frac. } M_d \times \text{Post}_t + \beta_L \text{Frac. } L_d \times \text{Post}_t + \varepsilon_{dt} \tag{21}$$

where Y_{dt} is log of nightlights or log of forest coverage in district d (in state s) in year t. As before, $Post_t$ is a dummy variable that takes the value 1 for the post-2004 period, and 0 otherwise. Frac. M_d and Frac. L_d are the fraction of middle- and large-sized applications received from a district d in the pre-policy years, i.e., before 2004. The coefficient of interest is β_M that measures whether nightlights and forest cover changed differentially in the post period for districts with more mid-sized projects. Regressions include district fixed effects, along with either year or state-year fixed effects.

Table 5 reports the results. First, Columns 1 and 2 show no statistically significant evidence that decentralization led to differential declines in forest cover for more-exposed districts. This result aligns with our structural model findings (Section 5.3), which indicated a modest net

Table 5—Impact of Decentralization

	Ln(Forest Area)		Ln(Night Lights)	
	(1)	(2)	(3)	(4)
Frac. Medium App. × Post	0.035	-0.044	-0.055*	-0.117***
	(0.07)	(0.06)	(0.03)	(0.02)
Frac. Large App. × Post	-0.065	-0.135**	0.023	-0.007
	(0.06)	(0.06)	(0.03)	(0.02)
R2	0.92	0.95	0.92	0.97
N	2358	2348	3904	3883
District FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No
State-Year FE	No	Yes	No	Yes

Notes: The outcome variables are the (log) forest area and (log) night-lights in a district d in a year t in Columns 1 and 2 respectively. Night Lights data is available from 1994-2009, while the Forest Cover data is available from 2000-2009. Frac. Medium App. and Frac. Large App. are the fraction of mid-sized and large-sized projects received by a district d in the years prior to the policy reform (2004). Post takes the value 1 for years after 2004 and 0 otherwise. All regressions control for district fixed effects. Columns (1) and (3) control for year fixed effects, while Columns (2) and (4) control for state-year fixed effects. Robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

increase (approximately 3%) in aggregate deforestation following decentralization, too small to detect empirically with precision. However, these districts did experience lower growth of nightlights (Columns 3 and 4). This is consistent with our previous analysis arguing that decentralization led to lower quality of economic projects being implemented.

7.2 Rationalizing the Aggregate Impact of Decentralization

Our structural calibration provides a clear theoretical rationale for these empirical findings. As discussed earlier (Sections 5 and 6), decentralization affects aggregate outcomes through two countervailing channels: first, a *direct conservation effect* that causes state governments to become relatively more stringent in approvals by placing a higher preference on conservation relative to economic development. Our structural estimates ($b^* = 0.89$) imply an 11% direct reduction in the approval probability *conditional* on applying.

A second channel — *an adverse selection effect* — speaks to the lower cost of application, λ, that along with b^*, drives the selection of applied projects in equilibrium. Our estimates indicate that decentralization simultaneously reduces applicants' costs of applying to state governments ($\lambda = 0.85$) as well, thus increasing the volume of project proposals, especially lower-quality ones. Quantitatively, this adverse selection channel leads to an 18% increase in total applications ($\sqrt{\lambda/b^*}^{-\theta} = 1.18$).

When combined, these two effects yield an overall reduction in average approval probabilities by 13% ($\sqrt{b^*\lambda} = 0.87$). However, because application volume increased by 18%, the net result

is a modest aggregate increase in deforestation of approximately 3% ($0.87 * 1.18 - 1 = 0.03$). This relatively small net increase helps rationalize why we do not find significant empirical evidence of increased forest cover loss in districts more exposed to decentralization (Table 5). Yet, while the overall deforestation effect is modest, our model predicts — and our empirical analysis on lower nightlight growth confirms — a lower economic development, potentially arising from approved projects. This occurs because decentralization induces adverse selection, causing a reduction in the average quality of projects proposed and approved.

Taken together, our theoretical and empirical analyses demonstrate clearly that decentralization, while intended to empower state governments with localized decision-making authority, can inadvertently result in fewer economically beneficial projects being approved and executed. At the same time, any potential environmental gains are largely offset by an increased volume of lower-quality applications, resulting in only minor aggregate changes in deforestation outcomes. Our findings therefore highlight the complexity of decentralizing environmental governance: while decentralization promotes local accountability and stricter environmental oversight, the unintended consequences, particularly resulting from lower application costs, may undermine intended policy benefits and lower economic growth.

8 Extension of the Model: Selection vs Sorting at Policy Threshold

Our baseline model emphasizes the *selection* effect, wherein changes in application costs and governmental preferences alter the overall volume and quality of projects submitted. However, because decentralization is implemented through specific size thresholds (20 Ha. and 40 Ha.), applicants might strategically adjust their proposed project sizes — "sorting" — to target a preferred approval authority. Empirically, Figure 3 clearly illustrates this sorting behavior, with discontinuities in application densities at both thresholds.

To examine the impact and relative importance of sorting, we extend our baseline model (in Section 4) to allow for applicants to manipulate the size of their project to apply to a different level of government. This allows us to quantify the relative importance of the selection versus sorting channels around the policy-relevant thresholds.

Setup of the Extended Model

Consider an applicant with a project defined by true quality and size $\{z, S\}$. Given this true size, let g be the government that would be the approving authority. Applicants, however, may find it beneficial to manipulate their reported project size to S', to shift the approval probability from one government to the other. The key gain from manipulation arises from differences in preferences for conservation (b_g) and application costs (λ_g).[13]

[13]For completeness of the argument, note that manipulation will also change the net valuation of the project from $\{\phi(S), \phi_A(S)\}$ to $\{\phi(S'), \phi_A(S')\}$. However, for exposition purposes, we assume that these functions are

Sorting, however, is not costless. We introduce a sorting cost, denoted by $c_M(S)$, reflecting the logistical or administrative effort required to alter project size. We define the relative sorting cost as $\tau(S) = c_M(S)/c_A(S)$, where $\tau(S)$ increases with project size ($\tau'(S) > 0$). This implies that larger projects are harder (more costly) to manipulate. To ensure realistic sorting behavior, we assume sorting costs are sufficiently high to prevent universal manipulation across the threshold, specifically requiring $\tau(S) > |b - \lambda|$.

Under these assumptions, we derive two important theoretical predictions discussed below. First, we show that applicants will never strategically manipulate project sizes upward (from state to central government), as long as sorting costs are positive and sufficiently large i.e., $\tau(S) > b-\lambda$. Second, applicants with sufficiently high-quality projects may strategically downsize proposals from the central government's jurisdiction into the state's jurisdiction to benefit from lower application costs ($\lambda < 1$). This strategic downsizing generates a discontinuous jump in application densities precisely below the threshold.

Lemma 5 *An applicant would never want to manipulate to move from a state government to the central government as long as $\tau(S) > b - \lambda$.*

See Appendix B.6 for the proof.

Lemma 6 *All projects with a quality $z \geq z^*_M(S)$ will manipulate their projects from the center to state government, where:*

$$z^*_M(S) \equiv M z^*_c(S) = \sqrt{\frac{\lambda + \tau(S) - 1}{b - 1}} \times z^*_c(S). \tag{22}$$

Moreover, the incentive to manipulate decreases with the size of the project.

See Appendix B.7 for the proof.

Given this, we can quantify the relative importance of selection versus sorting effects empirically by comparing observed application densities around the 40 Ha. threshold before and after decentralization. Specifically, that the observed density ratio at this threshold (ξ_{1r}/ξ_{0c}) can be decomposed precisely into a selection and sorting component, as discussed in the lemma below.

Lemma 7 *The ratio of density of projects around the 40 Ha. threshold can be decomposed into sorting and selection, given by:*

$$\frac{\xi_{1r}}{\xi_{0c}} = \underbrace{\left[M(40)\sqrt{\frac{1}{\alpha_c \beta_c}}\right]^{-\theta}}_{\textit{Sorting}} + \underbrace{\left[\sqrt{\frac{\lambda}{b}}\sqrt{\frac{1}{\alpha_r \beta_r}}\right]^{-\theta}}_{\textit{Selection}} \tag{23}$$

sufficiently concave near the policy thresholds such that effect of these marginal changes in S on project benefits and application costs can be ignored to a first order effect. Instead, the dominant incentive for sorting derives directly from differences in b_g and λ_g.

See Appendix **??** for the proof.[14] The empirical densities around the threshold and the calibrated values of b and λ from Section 5 allow us to use Equation (23) to quantify the relative importance of selection ($M(40)^{-\theta}$). We find that sorting (strategic manipulation) accounts for approximately 13% of the increase in application density observed at the 40 Ha. threshold, while general selection effects account for roughly 87%. Thus, while sorting around the threshold is empirically evident, our results indicate that the selection effects driven by overall changes in preferences and application costs overwhelmingly dominate the empirical patterns observed in our data.

9 Conclusion

This paper studies how decentralizing the authority to approve legal deforestation projects affects the balance between economic development and forest conservation. Exploiting a 2004 reform in India that shifted approval responsibility for mid-sized forest diversion projects (20–40 Ha.) from the central to state governments, we find that decentralization increased application volumes but reduced approval rates. We develop and estimate a structural model of endogenous application and approval decisions using administrative data on the universe of forest diversion proposals. Our estimates suggest that state governments place greater weight on conservation but are also more accessible to applicants, who face significantly lower application costs. This leads to more—but lower-quality—applications, resulting in a modest increase in deforestation and a decline in the local economic value of approved projects. These findings are consistent with evidence from project-level quality indicators, delays in approval processing, and reduced post-reform nightlight growth.

We further show that the effects of decentralization vary systematically with local institutional conditions. In states with higher corruption, applicants face lower costs of applying, while in forest-rich districts, governments display stronger conservation preferences. Extending our model to a dynamic setting, we show that although state governments may fundamentally value economic development more than the center in the long run, they choose more stringent short-run approval thresholds to screen a surge of lower-quality applications. These findings illustrate how decentralization shapes both sides of the decision-making process—altering who applies and how governments respond—and highlight the importance of considering administrative costs and selection dynamics in evaluating the consequences of institutional reform.

Our results have several policy implications. First, decentralization, even when coupled with more conservation-minded governments, may not improve environmental outcomes if it simultaneously lowers barriers to application and induces adverse selection. This highlights the need to complement decentralization with capacity-building measures—such as improving screening protocols, enhancing local monitoring systems, or introducing project-quality

[14] In Appendix B.7, we show that the density ratios at the 20 Ha. threshold cannot be completely decomposed into a sorting and selection effect. The selection effect appears multiplicatively with the sorting effect, which limits our ability to empirically estimate the relative importance of sorting at the 20 Ha. threshold directly.

thresholds. Second, the strong correlation between our estimated parameters and measures of institutional quality and forest stock suggests that decentralization should be tailored to local conditions. Uniform delegation of approval authority across states with varying administrative capacities and ecological value may result in uneven or unintended outcomes. A more differentiated approach to assigning authority, possibly based on state-level performance or safeguards, may yield more effective policy trade-offs.

The paper also opens up important directions for future research. First, while we estimate structural parameters that govern behavior on both sides of the application process, we do not directly observe how political economy factors—such as electoral cycles, lobbying, or rent-seeking—shape decisions in decentralized settings. Future work could explore how these political dynamics interact with institutional rules to affect project approval and land use outcomes. Second, while we focus on forestland diversion approvals, the framework developed here can be applied to other decentralized regulatory settings involving project evaluation and permitting—such as environmental impact assessments, mining licenses, or land conversion in urban contexts. Third, given that decentralization appears to shift the nature rather than the volume of development, understanding the long-term distributional consequences—who benefits from approved projects and who bears the environmental costs—remains an important open question. Ultimately, our findings underscore that institutional reforms—especially those that change who decides and who applies—must be evaluated not only in terms of intentions but also in terms of how they reshape selection, incentives, and accountability. In contexts where legal deforestation is regulated through bureaucratic approval, decentralization does not automatically lead to more sustainable outcomes. The success of such reforms depends critically on aligning the design of governance structures with both local administrative capacity and broader ecological and economic goals.

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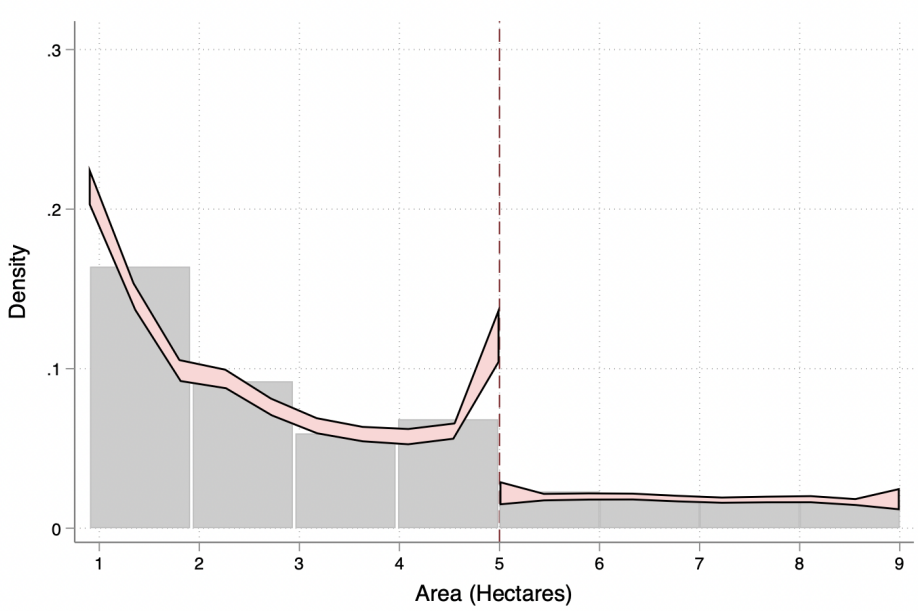
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APPENDIX

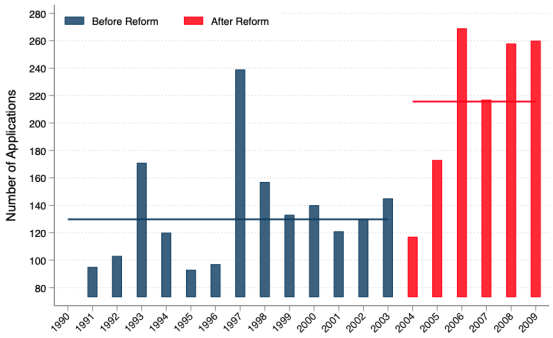
A Tables and Figures

Figure A1—Density of Applications at 5 Ha.

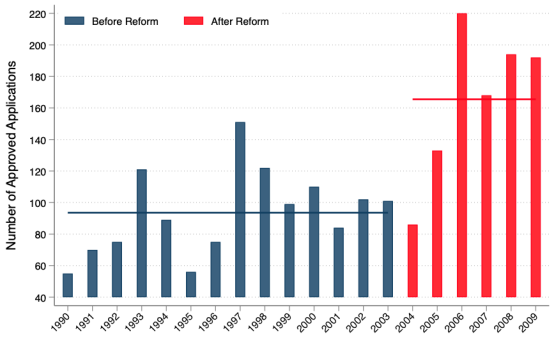


Notes: The above figure shows the discontinuity in the density of applications at 5 Ha. before the policy reform.

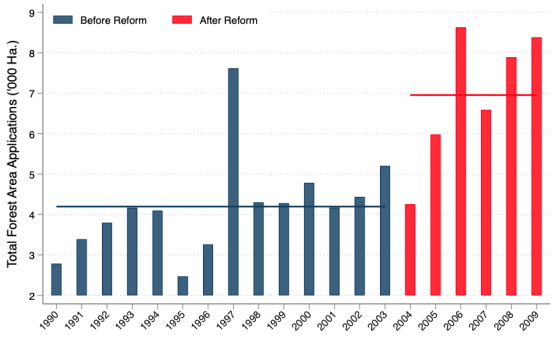
Figure A2—Total Volume and Area of Projects Over Time



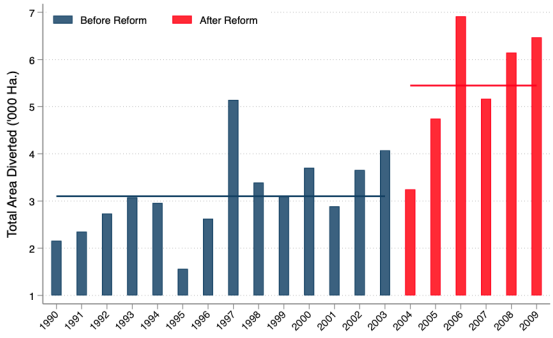
(a) Number of Total Applications



(b) Number of Approved Applications



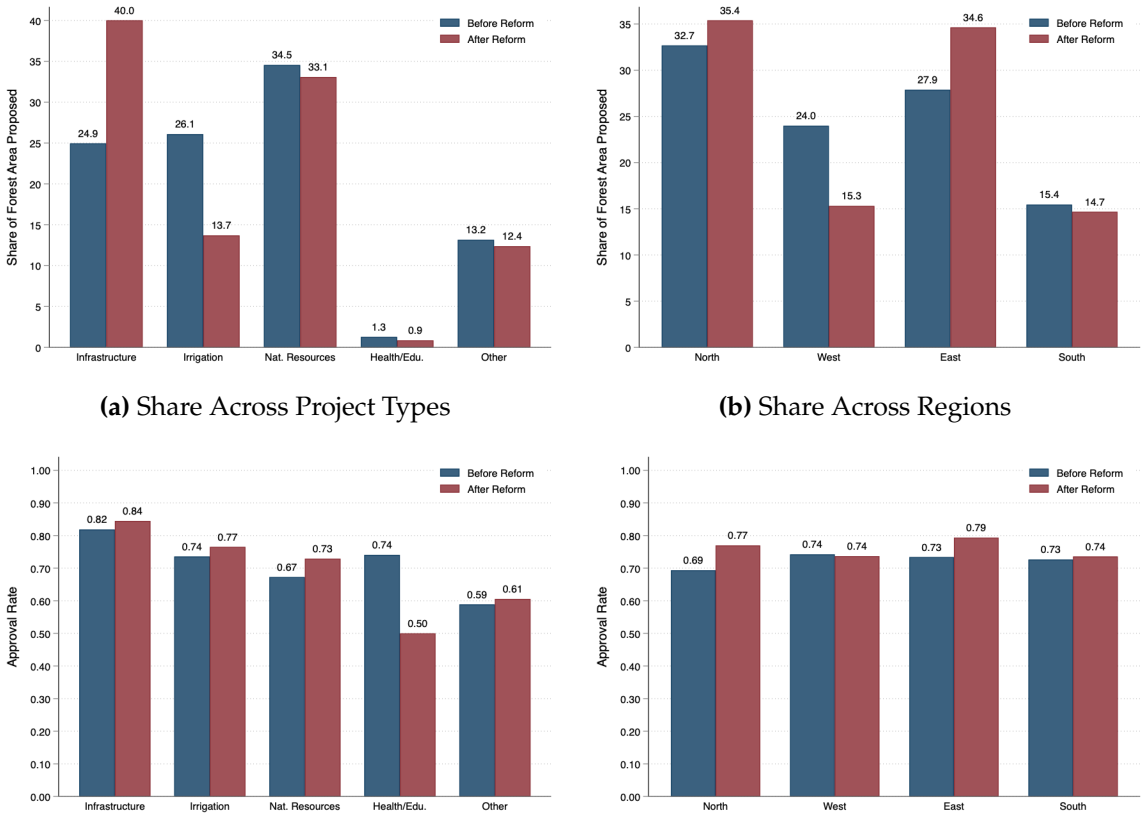
(c) Area of Total Applications



(d) Area of Approved Applications

Notes: The above figure shows the distribution of the number of applications and the area proposed for each year. Figures (a) and (b) show the total and approved number of applications in each year. Figures (c) and (d) report the total proposed and approved area of deforestation in a year.

Figure A3—Share of Applications by Area and Their Approval Rates



(a) Share Across Project Types

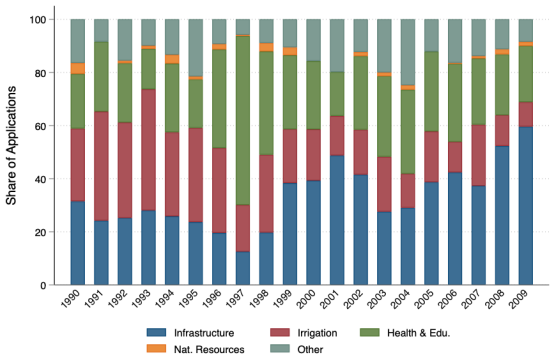
(b) Share Across Regions

(c) Approval Rates Across Project Types

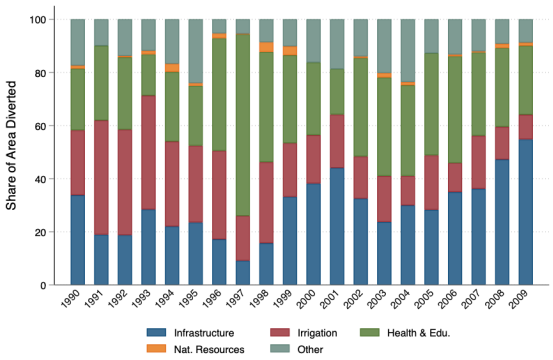
(d) Approval Rates Across Regions

Notes: Figures (a) and (b) report the share of area proposed across different project categories (Figure a) and across regions (Figure b). Figures (c) and (d) then report the average approval probability across project categories and regions respectively. The blue and red bars show the averages before and after the policy reform.

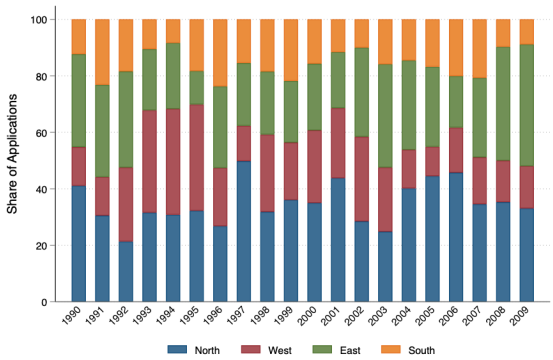
Figure A4—Volume and Area Across Regions and Project Categories



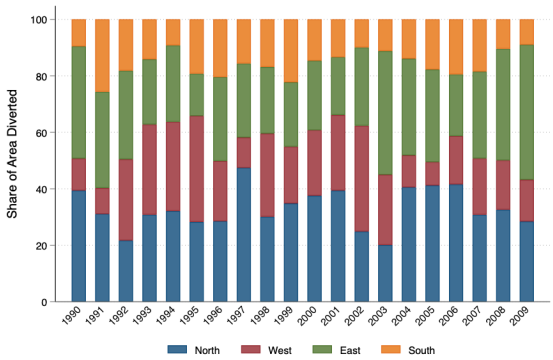
(a) Applications by Project Type



(b) Total Area by Project Type



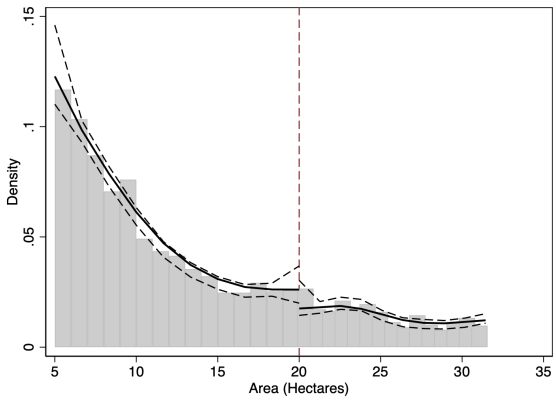
(c) Applications by Regions



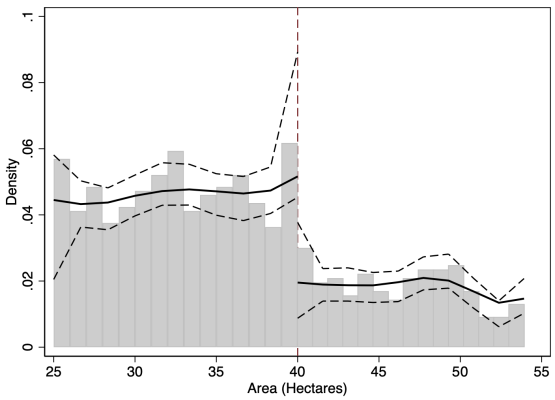
(d) Total Area by Regions

Notes: The above figure shows the number of applications and the area proposed for each year by project type (Figures a and b) and across regions (Figures c and d).

Figure A5—Density of Applications (2014-2021)



(a) At the 20 Ha. Threshold



(b) At the 40 Ha. Threshold

Notes: Figures (a) and (b) reports the discontinuity in the density of applications received at the 20 Ha. and 40 Ha. thresholds respectively. The sample is the universe of applications received between 2014-2021.

Table A1—Classification of States and Regions

Region	States
(1)	(2)
North	Chandigarh, Delhi, Haryana, Himachal Pradesh, Madhya Pradesh, Punjab, Rajasthan, Uttar Pradesh, Uttarakhand
West	Maharashtra, Goa, Gujarat
East	Arunachal Pradesh, Assam, Bihar, Chhattisgarh, Jharkhand, Manipur, Meghalaya, Mizoram, Odisha, Sikkim, Tripura, West Bengal
South	Andaman and Nicobar Islands, Andhra Pradesh, Karnataka, Kerala, Tamil Nadu, Telangana

Notes: The above table shows the classification of Indian states (Column 2) into four regions (Column 1).

Table A2—Approving Authority for Different Sized Projects

Category	Size	Before 2004	After 2004
Small	10-20 Ha.	State Govt.	State Govt.
Middle	21-40 Ha.	Central Govt.	State Govt.
Large	41-100 Ha.	Central Govt.	Central Govt.

Notes: The above table report the primary approving authority for projects according to their project size before and after the 2004 policy amendment.

Table A3—Values of (θ, b, λ) Based on Different Sample Restrictions

	θ	b	λ	$\sqrt{\lambda/b}$	$\sqrt{b\lambda}$
Whole Sample, Both	7.70	0.890	0.854	0.980	0.872
Whole Sample, Pre-Period	6.85	0.892	0.852	0.977	0.872
Whole Sample, Post-Period	8.22	0.889	0.855	0.981	0.872
Restricted, Both	7.28	0.891	0.853	0.978	0.872
Restricted, Pre-Period	6.29	0.894	0.850	0.975	0.872
Restricted, Post-Period	8.34	0.888	0.855	0.981	0.872
Restricted, Both	7.28	0.891	0.853	0.978	0.872

Notes: The sample restrictions are informative for calibrating different values of θ. Whole sample uses the entire sample while the Restricted sample excludes those applications between 15-25 Ha. Both pools the applications across both the pre- and post-policy period, while Pre-period and Post-period restricts them to the pre- and post-periods respectively.

Table A4—Approval Rates and Forest Cover (Restricted Sample)

	Below Median		Above Median	
	(1)	(2)	(3)	(4)
Middle	-0.01	-0.01	0.09***	0.10***
	(0.04)	(0.04)	(0.03)	(0.03)
Large	-0.01	-0.01	0.14**	0.11**
	(0.05)	(0.05)	(0.05)	(0.04)
Middle × Post	0.08***	0.08***	-0.13*	-0.15**
	(0.01)	(0.02)	(0.06)	(0.06)
Large × Post	0.09	0.10	-0.04	-0.04
	(0.05)	(0.06)	(0.03)	(0.04)
R2	0.09	0.15	0.08	0.15
N	1169	1138	1248	1205
State FE	Yes	No	Yes	No
Category FE	Yes	No	Yes	No
Year FE	Year	Yes	Year	Yes
State x Cat. FE	No	Yes	No	Yes

Notes: Data is at the level of project-year. All projects with area 10-100 Ha. over the time period 1990-2009 are in the sample. We exclude projects in a ±5 Ha. band around the policy thresholds. The dependent variable is a dummy variable that takes the value 1 if the project was approved and 0 otherwise. Middle (Large) is a dummy that takes value one if the project area is between 20-40 Ha. (40-100 Ha.). Post is an indicator for years 2004 and after. In Columns (1) and (2), we restrict the sample to districts with below-median forest cover in the year 2000. Columns (3) and (4) restrict the sample to districts with above-median forest cover in the year 2000. All regressions include year fixed effects. Columns (1) and (3) have state and project category fixed effects, while Columns (2) and (4) have state-category fixed effects. Standard errors clustered at the district and project-category level are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A5—Approval Rates and Nightlights (Restricted Sample)

	1(Project Approved)					
	Below Median			Above Median		
	(1)	(2)	(3)	(4)	(5)	(6)
Post	0.023			-0.015		
	(0.020)			(0.035)		
Middle	0.055	0.073	0.049	0.003	-0.005	-0.026
	(0.065)	(0.063)	(0.069)	(0.021)	(0.030)	(0.040)
Large	0.110*	0.117*	0.061	0.035	0.034	-0.004
	(0.054)	(0.056)	(0.056)	(0.045)	(0.045)	(0.031)
Middle × Post	-0.068	-0.082	-0.065	0.046***	0.053***	0.099**
	(0.061)	(0.070)	(0.073)	(0.015)	(0.012)	(0.042)
Large × Post	-0.035	-0.036	0.011	-0.006	-0.010	0.008
	(0.064)	(0.068)	(0.070)	(0.039)	(0.041)	(0.047)
Mean—Small,Pre	0.76	0.76	0.76	0.80	0.80	0.80
R2	0.08	0.10	0.19	0.08	0.11	0.20
N	874	874	829	795	795	761
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Category FE	Yes	Yes	No	Yes	Yes	No
Year FE	No	Yes	Yes	No	Yes	Yes
State x Cat. FE	No	No	Yes	No	No	Yes
Sample	Restricted	Restricted	Restricted	Restricted	Restricted	Restricted

Notes: Data is at the level of project-year. All projects between the years 1990-2009 with area 10-100 Ha., except those between 16-24 Ha. and 36-44 Ha. are included in the sample. The dependent variable is a dummy that takes value one if the project was approved and is zero otherwise. Middle is a dummy that takes value one if the project area is between 20-40 hectares, and large if it is between 40-100 hectares. Below (Above) Median are binary variables that take the value 1 if the nightlights in a district in the year 1994 was below (above) median. The results are reported in Columns (1)-(3) and (4)-(6) respectively. Post is an indicator for years 2004 and after. All regressions include state and project category fixed effects and Columns (2) and (4) include year fixed effects. Standard errors clustered at the state and project-category level are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A6—Probit Specification: Approval Rates and Govt.

	1(Project Approved)			
	(1)	(2)	(3)	(4)
app				
Post	0.17*		0.24**	
	(0.09)		(0.11)	
Middle	0.31***	0.28***	0.27**	0.25**
	(0.10)	(0.09)	(0.11)	(0.11)
Large	0.26**	0.24**	0.33***	0.32***
	(0.11)	(0.10)	(0.09)	(0.09)
Middle × Post	-0.25*	-0.23*	-0.27*	-0.24*
	(0.14)	(0.12)	(0.15)	(0.15)
Large × Post	0.02	0.02	-0.01	0.00
	(0.16)	(0.13)	(0.12)	(0.12)
N	3111	3111	2165	2165
State x Cat. FE	Yes	Yes	Yes	Yes
Year FE	No	Yes	No	Yes
Sample	Whole	Whole	Restricted	Restricted

Notes: Data is at the level of project-year. All projects with area 10-100 hectares and between 1990-2009 are included in the sample. The dependent variable is a dummy that takes value one if the project was approved and is zero otherwise. We estimate a probit specification. Middle is a dummy that takes value one if the project area is between 20-40 hectares, and large if it is between 40-100 hectares. Columns (1) and (2) consider the full sample while the last two columns drop projects with area in the range 16-24 hectares and 36-44 hectares. Post is an indicator for years 2004 and after. All regressions includes state-project category fixed effects and Columns (2) and (4) additionally include year fixed effects. Standard errors clustered at the state and project-category level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A7—Time Required Until Stage 1 Project Approval

	Days to Approval					
	(1)	(2)	(3)	(4)	(5)	(6)
Post	-185.20***			-210.49***		
	(49.27)			(59.50)		
Middle	-83.38	-91.73*	-127.07***	-84.66	-97.90	-123.46*
	(53.23)	(47.74)	(43.15)	(71.59)	(69.49)	(70.55)
Large	6.25	1.47	-28.03	0.43	-2.30	-34.30
	(55.53)	(52.13)	(40.67)	(63.75)	(63.81)	(60.06)
Middle × Post	91.51*	93.85*	126.12**	86.83*	93.85*	117.72**
	(53.33)	(50.44)	(46.40)	(46.87)	(47.09)	(47.41)
Large × Post	24.41	19.57	46.43	17.63	10.51	45.36
	(68.14)	(68.20)	(63.95)	(66.41)	(68.83)	(75.26)
Mean—Small,Pre	614.82	614.82	614.82	626.68	626.68	626.68
R2	0.11	0.14	0.27	0.13	0.15	0.30
N	1949	1949	1850	1377	1377	1275
Cat. FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	No	Yes	Yes	No
Year FE	No	Yes	No	No	Yes	No
State x Year FE	No	No	Yes	No	No	Yes
Sample	Whole	Whole	Whole	Restricted	Restricted	Restricted

Notes: Data is at the level of project-year. All projects with area 10-100 hectares are in the sample. The time period is 1990-2009. The dependent variable is the total number of days until a Stage 1 Project has been approved. Middle is a dummy that takes value one if the project area is between 20-40 hectares, and large if it is between 40-100 hectares. Columns (1)-(3) consider the full sample while Columns (4)-(6) drop projects with area in the range 16-24 hectares and 36-44 hectares. Post is an indicator for years 2004 and after. All regressions include state and project category fixed effects. Columns (2) and (5) include year fixed effects and columns (3) and (6) have state-year and project category fixed effects. Standard errors clustered at the state level are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A8—Time Required Until Stage 2 Project Approval

	Days to Approval					
	(1)	(2)	(3)	(4)	(5)	(6)
Post	-251.31***			-271.52***		
	(44.51)			(68.93)		
Middle	-279.05***	-284.55***	-278.57***	-283.17***	-289.95***	-274.47***
	(57.05)	(55.39)	(63.22)	(57.16)	(59.71)	(61.87)
Large	-22.03	-18.46	-14.32	-27.34	-17.44	-7.33
	(61.52)	(62.89)	(46.30)	(67.11)	(72.25)	(69.38)
Middle × Post	180.30***	183.70***	189.40***	138.05*	132.71*	131.64
	(54.25)	(46.27)	(63.24)	(69.02)	(68.17)	(89.41)
Large × Post	117.38	129.61	131.11	88.98	82.94	87.45
	(82.04)	(90.09)	(94.01)	(106.84)	(112.72)	(139.30)
Mean—Small,Pre	1074.90	1074.90	1074.90	1057.96	1057.96	1057.96
R2	0.16	0.18	0.36	0.15	0.18	0.39
N	1958	1958	1876	1370	1370	1289
Cat. FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	No	Yes	Yes	No
Year FE	No	Yes	No	No	Yes	No
State x Year FE	No	No	Yes	No	No	Yes
Sample	Whole	Whole	Whole	Restricted	Restricted	Restricted

Notes: Data is at the level of project-year. All projects with area 10-100 hectares are in the sample. The time period is 1990-2009. The dependent variable is the total number of days until a Stage 2 Project has been approved. Middle is a dummy that takes value one if the project area is between 20-40 hectares, and large if it is between 40-100 hectares. Columns (1)-(3) consider the full sample while the last three columns drop projects with area in the range 16-24 hectares and 36-44 hectares. Post is an indicator for years 2004 and after. All regressions include state and project category fixed effects. Columns (2) and (5) include year fixed effects and Columns (3) and (6) have state-year and project category fixed effects. Standard errors clustered at the state level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A9—District Level Forest Coverage Predicts Conservation Preferences

	Preference for conservation	
	(1)	(2)
Forest Coverage (2005)	0.179***	0.419***
	(0.029)	(0.058)
Mean Dep. Var.	0.15	0.15
Observations	12,246	12,246
R-squared	0.013	0.125
State FE	No	Yes

Notes: The dataset is Rural Economic and Demographic Survey (REDS) 2006. The dependent variable is a dummy that takes value one if the respondent in the REDS said "Yes" to the following question: "Imagine this: Govt. decides to contribute an additional Rupees 1 lakh to solve one local problem – but only if the majority of village households contribute 100 Rupee each. Imagine that almost enough people are willing to contribute and your decision to contribute or not, will decide the outcome – would you consider contributing Rs. 100 if the issue was natural resource management?" Forest Coverage (2005), computed from VCF data, is the percentage of forest coverage in 2005 in the district in which the respondent lives. Both columns control for respondent's gender, age, age squared and years of education and area of district. Column (2) additionally has state fixed effects. Robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A10—Threshold Project Quality and Approving Government

	Log Employment Generated		
	(1)	(2)	(3)
	0 Pct.	1 Pct.	2 Pct.
RD Estimate	1.61	1.74	1.73
	(0.84)	(0.87)	(0.86)
Con. p-value	0.054	0.045	0.045
Robust p-value	0.067	0.075	0.077
Bandwidth	12.63	11.90	12.02
N	91	91	91
BW Type	CCT	CCT	CCT

Notes: The above table reports the RD estimate using Calonico, Cattaneo and Titiunik (2014) for minimum project quality around the 40 Ha. policy threshold using the universe of projects between 2014-2021. Threshold project quality is measured using the minimum, 1st, 2nd and 3rd percentiles of log employment generated across all projects of size S in Columns (1)-(4) respectively. Conventional and robust p-values are reported in the rows below.

B Mathematical Proofs and Derivations

B.1 Approval Decision of the Government

Lemma 1 states that *"conditional on size, higher quality projects are more likely to be approved i.e., $\partial P/\partial z > 0$. Moreover, conditional on the quality of the project, larger projects are less likely to be approved i.e., $\partial P/\partial S < 0$."*

***Proof*:** Given that $F'_\eta(x) > 0$, it is obvious to see that $\partial P_g/\partial z > 0$. Let e_ϕ be the elasticity of ϕ w.r.t. S and let e_q and e_c be defined similarly for the functions q and c. Then, $e_\phi = e_q - e_c$. Additionally,

$$e_q = \frac{q^{'}(S)S}{q(S)} < 1 \quad \text{since } q(S) \text{ is strictly concave, and}$$

$$e_c = \frac{c^{'}(S)S}{c(S)} \geq 1 \quad \text{since } c(S) \text{ is weakly convex}$$

which implies $e_\phi < 0$. Lastly,

$$\frac{\partial P}{\partial S} = \underbrace{\frac{\partial F_\eta}{\partial \phi}}_{>0} \times \underbrace{\frac{\partial \phi}{\partial S}}_{<0} < 0$$

■

B.2 Threshold Project Quality and Project Size

Lemma 2 states that *"the threshold quality is increasing int he size of the project i.e., $\partial z_g^*/\partial S > 0$."*
***Proof*:** Rearranging Equations (2) and (4) we have:

$$\ln F_\eta(z_g^*\phi(S)) + \ln z_g^* + \ln \psi(S) = \ln \lambda_g$$

$$\frac{b_g F'_\eta(x)}{F_\eta(x)}\left[\phi(S)\frac{\partial z_g^*}{\partial S} + z_g^*\phi'(S)\right] + \frac{1}{z_g^*}\frac{\partial z_g^*}{\partial S} + \frac{\phi'(S)}{\phi(S)} = 0 \text{ (Differentiating both sides)}$$

$$\underbrace{\left[\frac{F'_\eta(x)}{F_\eta(x)} b_g \phi(S) + \frac{1}{z_g^*}\right]}_{>0}\frac{\partial z_g^*}{\partial S} = -\left\{\underbrace{\frac{1}{\phi(S)}}_{>0} + \underbrace{\frac{F'_\eta(x)}{F_\eta(x)}}_{>0} b_g z_g^*\right\}\underbrace{\phi'(S)}_{<0} > 0$$

■

B.3 Parameterization of the Model

We now provide details on parameterization of the model. As discussed in the paper, we assume $z \sim Pareto(\theta)$ i.e., $F(z) = 1 - z^{-\theta}$, and that $\eta \sim U(0, K)$. Based on these assumptions, we can derive Equations (**??**)-(**??**) from their corresponding theoretical counterparts. Turning to Equations (**??**), we use a property of the Pareto distribution where if $x \sim Pareto(\theta)$, then

for any $a < \theta$, $E(x^a | x \geq x^*) = \frac{\theta}{\theta - a}(x^*)^a$. This implies that the average approval probability is given by:

$$\begin{aligned}
\overline{P}_g(S) &= \int_{z \geq z_g^*(S)} P_g(z, S) \frac{dF_z(z)}{1 - F_z(z_g^*(S))} \\
&= b_g \phi(S) \int_{z \geq z_g^*(S)} \frac{z dF_z(z)}{1 - F_z(z_g^*(S))} \\
&= b_g \phi(S) E(z | z \geq z_g^*) \\
&= \frac{\theta}{\theta - 1} b_g \phi(S) \times z_g^* = \frac{\theta}{\theta - 1} P_g(z_g^*)
\end{aligned}$$

In a similar way, we can calculate the variance of approval probability (Equation 11) as follows:

$$\begin{aligned}
V(P_g) &= \int_{z \geq z_g^*(S)} \left[P_g(z, S) - \overline{P}_g(S) \right]^2 \frac{dF_z(z)}{1 - F_z(z_g^*(S))} \\
&= \int_{z \geq z_g^*(S)} P_g^2 \frac{dF_z(z)}{1 - F_z(z_g^*)} + \overline{P}_g^2 - 2\overline{P}_g \underbrace{\int_{z \geq z_g^*} P_g \frac{dF_z(z)}{1 - F_z(z_g^*)}}_{= \overline{P}_g} \\
&= \int_{z \geq z_g^*(S)} P_g^2 \frac{dF_z(z)}{1 - F_z(z_g^*)} - \overline{P}_g^2 \qquad \text{(See Equation ??)} \\
&= \frac{\theta}{\theta - 2} \overline{P}_g^2 - \overline{P}_g^2 \\
&= \frac{2}{\theta - 2} \overline{P}_g^2
\end{aligned}$$

B.4 Proof of Lemma 4

Lemma 4 states that: *Under the assumption that $\eta_t \sim$ Uniform$(0, 1)$ and $z \sim Pareto(\theta)$, the optimal choice of b_{gt}^* can be given by:*

$$b_{gt}^* = \omega_g^2 \lambda_g \kappa(\mathcal{F}_t) \quad \textit{where } \kappa(\mathcal{F}_{gt}) = \left[\frac{\theta}{\theta + 1} \frac{1 - \beta}{c_0} \frac{\Gamma_V(\mathcal{F}_{gt})}{\Gamma_D(\mathcal{F}_{gt})} \right]^2$$

Using these distributional assumptions, we get that:

$$D_{gt} = b_{gt}^{\frac{1+\theta}{2}} \lambda_g^{\frac{1-\theta}{2}} \Gamma_D(\mathcal{F}_{gt}), \text{ and}$$

$$V_{gt} = b_{gt}^{\frac{\theta}{2}} \lambda_g^{1 - \frac{\theta}{2}} \Gamma_V(\mathcal{F}_{gt})$$

$$\text{where } \Gamma_D(\mathcal{F}_{gt}) = \frac{\theta}{\theta - 1} \int_S S \phi(S)^{\frac{\theta+1}{2}} \phi_A(S)^{\frac{\theta-1}{2}} dG_{\mathcal{F}_{gt}}(S)$$

$$\text{and } \Gamma_V(\mathcal{F}_{gt}) = \frac{\theta}{\theta - 2} \int_S q(S) \phi(S)^{\frac{\theta}{2}} \phi_A(S)^{\frac{\theta}{2} - 1} dG_{\mathcal{F}_{gt}}(S)$$

Let $\{b^*_{gt}\}$ be the solution to Equation (10). The Bellman equation can be written as:

$$\Pi_g(\mathcal{F}) = \max_{b_g} \omega_g V + c_0(\mathcal{F} - D) + \beta \Pi_g(\mathcal{F} - D)$$

FOC w.r.t. b_g gives us

$$\frac{\theta}{2}\omega_g b_g^{\frac{\theta}{2}-1}\lambda_g^{1-\frac{\theta}{2}}\Gamma_V(\mathcal{F}) - (c_0 + \beta\Pi_g^{'}(\mathcal{F} - D))\left(\frac{\theta}{2}+\frac{1}{2}\right) b_g^{\frac{\theta-1}{2}}\lambda_g^{\frac{1-\theta}{2}}\Gamma_D(\mathcal{F}) = 0 \tag{24}$$

Let $V^*(\mathcal{F})$ and $D^*(\mathcal{F})$ be the optimized values of V and D. Then,

$$\Pi_g(\mathcal{F}) = \omega_g V^*(\mathcal{F}) + c_0(\mathcal{F} - D^*(\mathcal{F})) + \beta\Pi_g(\mathcal{F} - D^*(\mathcal{F}))$$

Differentiating w.r.t. $\mathcal{F}$ we get,

$$\Pi_g^{'}(\mathcal{F}) = c_0 + \beta\Pi_g^{'}(\mathcal{F} - D^*(\mathcal{F}))$$

$$\Rightarrow \quad \Pi_g^{'}(\mathcal{F}) - \beta\Pi_g^{'}(\mathcal{F} - D^*(\mathcal{F})) = c_0$$

Therefore $\Pi_g^{'}(\mathcal{F})$ is constant. Let $\Pi_g^{'}(\mathcal{F}) = a$. Then,

$$a = \frac{c_0}{1-\beta}$$

Using this in Equation (24) gives us

$$\frac{\theta}{2}\omega_g b_g^{\frac{\theta}{2}-1}\lambda_g^{1-\frac{\theta}{2}}\Gamma_V(\mathcal{F}) = \frac{c_0}{1-\beta}\left(\frac{\theta}{2}+\frac{1}{2}\right) b_g^{\frac{\theta-1}{2}}\lambda_g^{\frac{1-\theta}{2}}\Gamma_D(\mathcal{F})$$

$$\Rightarrow \quad b_g^{\frac{1}{2}}\Gamma_D(\mathcal{F}) = \omega_g \frac{\theta}{\theta+1}\frac{1-\beta}{c_0}\lambda_g^{\frac{1}{2}}\Gamma_V(\mathcal{F})$$

$$\Rightarrow \quad b_g^* = \omega_g^2\lambda_g\kappa(\mathcal{F}) \quad \text{where } \kappa(\mathcal{F}) = \left[\frac{\theta}{\theta+1}\frac{1-\beta}{c_0}\frac{\Gamma_V(\mathcal{F})}{\Gamma_D(\mathcal{F})}\right]^2$$

B.5 Manipulation from the Regional to Central Government

We now prove Lemma 4. Consider a manipulation of an applicant from the regional government to the Central Government. In that case there are two conditional that should hold. First, that the application should be "feasible" for the applicant under the Central government i.e., $V_c(z, S') \geq 0$ and second, it should be incentive compatible i.e., $V_c(z, S') \geq V_r(z, S)$. Mathematically, they can be expressed as follows:

$$V_c(z, S') \approx z\phi(S) \times zq(S) - c_A(S) - c_M(S) \geq 0 \qquad \text{(Individual Rationality)}$$

$$V_c(z, S') \approx z\phi(S) \times zq(S) - c_A(S) - c_M(S) \geq bz\phi(S) \times zq(S) - \lambda c_A(S) \qquad \text{(Incentive Compatibility)}$$

Re-arranging the IC constraint implies that $(b-1)z^2\phi(s)\psi(s) \leq (\lambda - 1) - \tau(S)$, where $\tau(S) = \frac{c_M(S)}{c_A(S)}$. IC is not satisfied as long as $b > \lambda - \tau(S)$ i.e., the costs of manipulation $\tau(S)$ are

sufficiently high.

B.6 Manipulation from Central to Regional Government

Consider manipulation of a project from the Central government to the Regional government. The feasibility and incentive compatibility constraints for this condition are as follows:

$$V_r(z, S') \approx bz\phi(S) \times zq(S) - \lambda c_A(S) - c_M(S) \geq 0 \quad \text{(Individual Rationality)}$$
$$V_r(z, S') \approx bz\phi(S) \times zq(S) - \lambda c_A(S) - c_M(S) \geq z\phi(S) \times zq(S) - c_A(S) \quad \text{(Incentive Compatibility)}$$

IR implies

$$bz^2\phi(S)\psi(S) \geq \lambda + \tau(S)$$

IC implies

$$(b-1)z^2\phi(S)\psi(S) \geq (\lambda - 1) + \tau(S)$$

Re-arranging both the constraints, we can calculate the productivity of the marginal project:

$$\begin{aligned}
z^*_{IR} &= \sqrt{\frac{\lambda + \tau(S)}{b}} \times \frac{1}{\sqrt{\phi(S)\psi(S)}} \\
z^*_{IC} &= \sqrt{\frac{\lambda + \tau(S) - 1}{b-1}} \times \frac{1}{\sqrt{\phi(S)\psi(S)}} \\
z^*_M &= \max\{z^*_{IR}, z^*_{IC}\} = \max\left\{\sqrt{\frac{\lambda + \tau(S)}{b}}, \sqrt{\frac{\lambda + \tau(S) - 1}{b-1}}\right\} \times \frac{1}{\sqrt{\phi(S)\psi(S)}} \\
&= \sqrt{\frac{\lambda + \tau(S) - 1}{b-1}} \times \frac{1}{\sqrt{\phi(S)\psi(S)}} = Mz^*_c
\end{aligned}$$

where the penultimate equality comes from the assumption that $\lambda + \tau(S) > b$, which is necessary since we observe positive mass to the right side of the threshold. If $\lambda + \tau(S) \leq b$ then all project to the right of 40 would sort to the left. Lastly, note that since $\tau'(S) > 0$ and $z^{*'}_c(S) > 0$, it implies that $z^{*'}_M(S) > 0$ i.e., the threshold productivity to manipulate is increasing in the size of the project. To put it another way, this implies that sorting is strongest for projects near the threshold and will decrease with increasing size.

B.7 Decomposition of Density Difference into Selection and Sorting

We now use this extended framework to decompose the discontinuous density observed in Section 3.1 into selection and sorting. We do this separately for 40 Ha. and 20 Ha.

Sorting at 40 Ha.: Note that from the model, the ratio of the density of projects in post- and pre-period to the left of the 40 Ha. threshold can be given by:

$$\begin{aligned}
\frac{\xi_{1r}}{\xi_{0c}} &= \frac{(1-F(z_M^*))+(1-F(z_{1r}^*))}{1-F(z_{0c}^*)} \\
&= M(40)^{-\theta}\left(\frac{z_{1c}^*}{z_{0c}^*}\right)^{-\theta} + \left(\frac{z_{1r}^*}{z_{0c}^*}\right)^{-\theta} && \text{(From Equation ??)} \\
&= \underbrace{\left[M(40)\sqrt{\frac{1}{\alpha_c\beta_c}}\right]^{-\theta}}_{\text{Sorting}} + \underbrace{\left[\sqrt{\frac{\lambda}{b}}\sqrt{\frac{1}{\alpha_r\beta_r}}\right]^{-\theta}}_{\text{Selection}} && \text{(From Equation 13)}
\end{aligned}$$

We use the empirical distributions of the density in the range [35,40] in pre and post periods to calculate their ratio which enables us to estimate the sorting effect $M(40)^{-\theta}$ since the selection effect ($\sqrt{\lambda/b}^{-\theta}$) and the time trends are already estimated. We find that about 13% of the difference in density at 40 Ha. in the post period can be explained by sorting.

Sorting at 20 Ha.: Consider the mass of projects to the *left* of the 20 Ha. threshold. Then the ratio of the density of projects in post- and pre-period can be given by:

$$\begin{aligned}
\frac{\xi_{0r}}{\xi_{1r}} &= \frac{(1-F(z_M^*))+(1-F(z_{0r}^*))}{1-F(z_{1r}^*)} \\
&= \frac{(M(20)z_{0c}^*)^{-\theta}+(z_{0r}^*)^{-\theta}}{(z_{1r}^*)^{-\theta}} \\
&= \left[M(20)^{-\theta}\left(\frac{z_{1r}^*}{z_{0r}^*}\times\frac{z_{0r}^*}{z_{0c}^*}\right)^{\theta} + \left(\frac{z_{1r}^*}{z_{0r}^*}\right)^{\theta}\right] \\
&= \left[\underbrace{M(20)^{-\theta}}_{Sorting} + \underbrace{\left(\sqrt{\frac{\lambda}{b}}\right)^{-\theta}}_{Selection}\right] \times \underbrace{\frac{1}{\left(\sqrt{\frac{\lambda}{b}}\sqrt{\frac{1}{\alpha_r\beta_r}}\right)^{-\theta}}}_{Selection}
\end{aligned}$$

The equation above shows that the density ratios at 20 Ha. threshold can not be completely decomposed into sorting and selection. In the RHS of the equation above, the selection effect appears multiplicatively with the sorting effect. Hence, we are unable to empirically estimate the relative importance of sorting at the 20 Ha. threshold.