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

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Abstract

With rapidly depleting natural resources, governments across the world face the task of balancing economic development with conservation efforts. We study how the governance structure surrounding environmental policy-making, specifically decentralization of natural resource management shapes this trade-off by examining the economic projects in India that required diversion of forest land and were submitted to the Indian government for approval. We compile the universe of proposal submissions and their application outcomes and exploit a policy reform that decentralized the approval authority for a certain size of projects from the Central to State governments. We find that decentralization significantly *increased* the number of applications, but *reduced* the probability of approval. Estimates from a structural model with endogenous applications and approvals indicate that while State governments (as compared to the Center) put a 6% *lower* weight on economic development (vis-a-vis conservation), they also have 11% *lower* application cost. This results in a lower quality and higher volume of projects being proposed and approved, resulting in more deforestation without much economic development. From the lens of a dynamic model, we show that while State governments *fundamentally* value economic development more, they optimally *choose* to be more stringent in approvals, in response to lower costs and more applications received by them.

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1 INTRODUCTION

With growing concerns surrounding natural resource depletion and associated climate change,[1] governments across the world face the task of balancing economic development with environmental conservation. This trade-off is particularly stark for many low and middle-income countries, who are vulnerable to climate change and yet aspire to catch up to the developed world. The governance structure surrounding the extraction and usage of natural resources is therefore of specific significance in these countries, since these institutional frameworks shape the incentives and behavior of all stakeholders, which ultimately determines the trajectory along which this trade-off gets resolved.

In this paper, we shed light on understanding this trade-off by examining the effect of a governance reform in India that expanded the scope of decentralized policy-making in the context of converting forest land for economic development projects. To elaborate on the context, any economic activity requiring diversion of forest land in India needs the approval of either Central or State governments, depending on the size of land to be diverted. This is a unique context therefore, where the government hierarchy (State vs Center) directly shapes the development-conservation trade-off. If the two types of governments weigh economic development (vis-a-vis conservation) differently, then it could affect the type (or quality) of projects that are proposed to, and approved by these government bodies, which could either exacerbate or attenuate the overall impact on economic development and deforestation.

Several studies in the literature have examined the impact of decentralization on environmental policy-making. For example, Burgess, Hansen, Olken, Potapov, and Sieber (2012) examine impact of decentralization on illegal deforestation in Indonesia, Lipscomb and Mobarak (2016) on water pollution in Brazil, Edmonds (2002) and Somanathan, Prabhakar, and Mehta (2009) on forest conservation in Nepal and India respectively. However, these studies tend to 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 context focuses on *legal* deforestation for the purposes of legitimate economic activity and thereby, provides us with a unique opportunity to study how governments at different levels trade-off environmental considerations with economic development differently and its consequences on the quality of projects that are proposed and approved.

To examine this question, we compile a rich administrative dataset in India that consists of the universe of proposals submitted to the Indian government for diversion of forest land for economic projects during the period 1990-2019. Spanning a period of three decades, these data contain detailed information on the location and parcel size of the forest land to be diverted, along with its intended economic use, and most importantly, the approval outcome of each project (along with other details). A unique policy change in 2004 allows us to study the effect of decentralization. To elaborate, historically, the approval decisions for smaller projects with an area of up to 20 hectares were made by State governments, while the Central government took the final call on larger projects (greater than 20 Ha.). The policy change in 2004 doubled this size threshold to 40 hectares, thus increasing the share of projects assessed by State governments (from 48% to 66%). For our main empirical analysis we restrict our attention to applications during 1990-2009.[2] We begin our analysis by exploiting this policy reform and establishing

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

[2]We do not use data after 2010 since The National Green Tribunal was established in 2010, which opened the window for citizens to challenge the governments' forestland diversion decisions. For some additional analysis, we utilize data from 2014-2019, which contains additional information about project quality.

two key empirical facts on the impact of this decentralization on project applications and approvals.

For the first empirical fact, we show an increase in the number of applications received in the 20-40 Ha. range when the approving authority was the State government (post 2004), as opposed to the Center (prior to 2004). We establish this in two ways: first, we document a clear shift up in the CDF of application size in the 20-40 Ha. range in the post-2004 period, with no such shift for projects smaller than 20 Ha. Second, we observe a discontinuously higher density of projects to the left of the 20 Ha. threshold before 2004, and similarly to the left of the 40 Ha. threshold after 2004.[3]

The second empirical fact we document is that State governments have in fact a *lower* probability of approving projects on average, as compared to the Center. Using a difference-in-differences specification, we find that the average approval probability of projects between 20-40 Ha. *falls* by 15 percent after the policy reform. Taken together, the above facts–more applications and a lower approval probability–suggest that the selection (or quality) of projects received by State governments have to be lower on average as compared to the Center. This could be because of a different preference that the State might have on the economic valuation of the project (as compared to the Center), or because applicants face a lower cost of applying to the State (relative to the Center), or both.

To examine these issues more rigorously, we develop a theoretical framework that models applicants' decision to apply and consequently, the government's decision to approve a project. Each project is characterized by its size (S) and quality (z), observable to the government but unobservable to researchers. An applicant with a project will trade-off the expected benefit from the project with a (government-specific) cost of application (denoted by λ_g) when deciding whether to apply. On the other hand, the key trade-off faced by a government g in making its approval decision is the preference weighted economic value of a project relative to the cost of deforestation (denoted by b_g). We solve for the optimal approval and application decisions by each government and applicant respectively, depending on governments' preference weight (b_g) and application cost (λ_g).

Our analysis unpacks several forces that are at play in this context to identify the parameters of interest. First, we point out that the approval probability for the same project could be different across Center and State due to the differential preference weights on project value in their payoff functions. Second, the cost of application could also be different, if, for example, an applicant is more likely to have connections with officials in the State government than the Center, or vice versa. This may result in different selection of projects being applied under different governments, which, in turn, could affect the average approval probability. Put together, it could produce a different distributions of applications and average probability of approval under each type of government.

Before we proceed, two important clarifications are in order. First, our baseline model is static in nature and hence a government's preference weight (b_g) is a 'fundamental' parameter. However (in Section 8.1), we extend the model to allow for a dynamic decision-making by the government i.e., for governments' past approval behavior to affect how they evaluate future projects. This endogenizes its preference for deforestation over time, which, as we discuss below, can meaningfully complement the static model. Second, we initially abstract away from any sorting that can arise from a threshold policy rule and focus on the selection problem instead. This is because while sorting would be limited to the neighborhood of the threshold, the selection effect is a more general concern in this context. In Section

[3] As one would expect, we do not find any discontinuity at 40 Ha. in the pre-2004 period and at 20 Ha. in the post-2004 period.

8.2 later, we extend our framework to allow for sorting around the threshold, and use our structural estimates to show that it can explain only around 13 percent of the change in the applications we see due to the policy change.

Under some parametric assumptions, we are able to identify (for each project size), the threshold quality (z^*) above which an applicant will apply. This in turn determines: (i) the size distribution of the applied projects; and (ii) the average approval probability as a function of project size. The policy reform in 2004 allows us to observe the empirical distribution of applications and their average approval probability for project size between 20-40 Ha. under both the Center (in the pre-period) and State (in the post-period). These moments map directly to the model, thus allowing us to identify the key structural parameters. In particular, we recover the weight that the State governments put (relative to the Center) on the economic value of projects (vis-a-vis conservation) i.e., $b \equiv b_{State}/b_{Center}$, and the relative cost of application under the State government relative to the Center i.e., $\lambda \equiv \lambda_{State}/\lambda_{Center}$.

Our structural estimates indicate that State governments put a lower weight on the project's economic value relative to the Center (or higher weight on conservation) by 6% ($b = 0.94$), reducing their average approval probability by around 8%. This implies that they appear to care more about conservation than the Center. However, we find that the application costs for State governments are also 11% lower as compared to the Center ($\lambda = 0.89$), which *increases* the mass of applications under State governments by 18%. This leads to an overall increase in deforestation by about 8%, indicating that the State's higher weight on conservation is overwhelmed by the endogenous increase in the number of lower quality projects that get approved.

We conduct a number of model validation exercises. First, we find that the fall in average approval probability due to decentralization as estimated from the model is very close to the reduced form results. Second, we show that consistent with our model predictions, the quality of applied and approved projects is indeed lower when the State government is the decision-maker. We measure this in two ways: first, the time taken to approve projects (conditional on the total number of applications) for the 20-40 Ha. projects (relative to the projects under 20 Ha.) significantly increases in the post-reform period. Additionally, we use application data from 2014-2019 that contain information about the expected employment generated from each project, if approved. Using the minimum employment generated for each project size as our measure of quality threshold (z^*), we show that the minimum employment generated exhibits a positive discontinuity at the size threshold of 40 Ha. as predicted by our model. Finally, we show that our parameter estimates correlate meaningfully with the characteristics of the local economy of the projects' locations. For example, for projects located in districts having a higher (lower) forest coverage at the baseline, the State government has a even higher (lower) weight on conservation vis-a-vis its economic value. Similarly, for projects located in districts having lower economic development at baseline, proxied by nightlights, the State puts 4% *higher* weight on economic value of the projects, suggesting that impact on local economy matter more for the State government than the Center. Finally, the estimates for application costs are lower for those states that are politically aligned with the Center, as well as those ones that have a Regional Office (that approves the project at the State level).

Taken together, our results imply that decentralization leads to a fall in the average quality of approved projects due to adverse selection driven by lower cost of application and a rise in deforestation. We confirm this implication by examining trends in district level forest cover and nightlights. We find that districts that are more exposed to the decentralization reform (due to greater prevalence of mid-sized projects at baseline) experience lower growth in nightlight and forest cover in the post-2004 period, though the result on forest cover is not statistically significant.

Our baseline model assumes that the government evaluates each project by using its exogenously specified preference weight (b_g). However, it is possible that the stock of forest resource as well as the previous approvals can impact how much a government cares about approving future projects i.e., b_g could be endogenous. We therefore develop a dynamic version of our static model, where the economy has a stock of forest resource, which depletes over time as governments approve projects for deforestation. A government in every period therefore, optimally chooses how to evaluate projects–by balancing a higher payoff from economic value generated from the approved projects with a lower payoff (both in the current period as well as in the future) from a reduced stock of forest. The preference weight (b_g) is therefore *endogenously* chosen in this model, and it changes over time as the forest stock depletes. However, we show that under the same parametric assumptions made in the static model, the ratio of State and Central governments' preference weight i.e., $b^* = b^*_{State}/b^*_{Center}$ is *constant* over time, implying that the estimates of our baseline model apply in the dynamic setting as well.

The dynamic model therefore provides two additional insights: first, even when governments can endogenously adjust its preference weight for economic development over time, the State government continues to be more stringent in its approval decisions than the Center (since $b < 1$), primarily to stem the increase in lower quality projects received due to lower application costs ($\lambda < 1$). Second, we show that the model allows us to recover the true fundamental preference weight for the State government's life-time payoff relative to the Center, which we denote by $\omega \equiv \omega_{State}/\omega_{Centre}$. Theoretically, we show that $\omega \propto b^*/\lambda$, which given our estimates for b and λ, imply $\omega = 1.03$. This indicates that in a dynamic context, even though the State fundamentally cares *more* about economic development, it *chooses* to value conservation more (i.e., choose $b^* < 1$) while evaluating projects in any given period. This is because applicants face substantially lower application costs for the State as compared to the Center ($\lambda < 1$), which generate more lower quality applications every period. An implication of this dynamic setting therefore is to show that simply knowing a government's preference weight on projects' economic value (b) alone does not indicate the nature of its fundamental preference (ω), but should be viewed in conjuction with the application costs (λ) as well.

Our paper contributes to several strands of the literature. Researchers and policymakers are increasingly studying reciprocal relationship between economic development and the environment (Jayachandran 2022, Balboni 2019, Asher, Garg, and Novosad 2020), triggering debates in less-developed countries about sustainable ways of developing, as well as understanding how individuals adapt to it (Kala 2017, Jack, Jayachandran, Kala, and Pande 2022). We contribute to this important discussion by focusing on the governance framework surrounding environmental policy making shaping this trade-off. Consequently, 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.

Moreover, 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 state.

With regard to 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. 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. As opposed to illegal activities undertaken by individuals (farmers for example) however, our focus is to examine the policy decisions for *legal* deforestation and how decentralization of the decision-making can impact it.

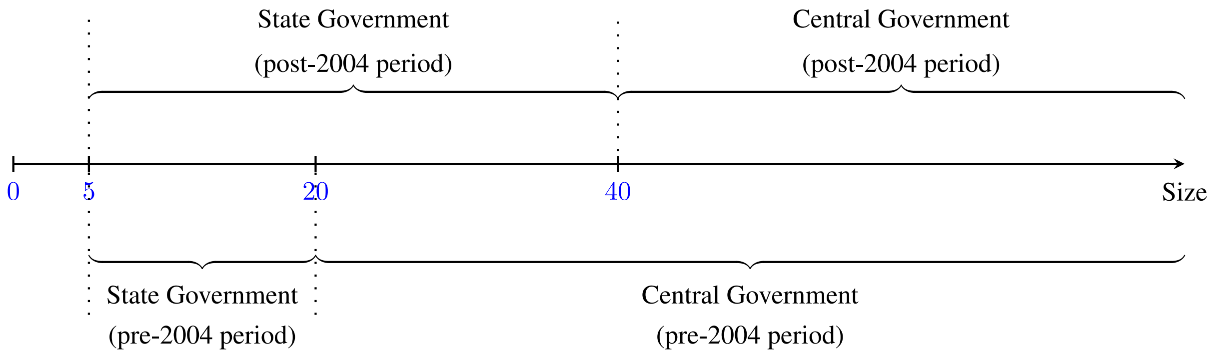
2 INSTITUTIONAL DETAILS AND DATA

2.1 BACKGROUND AND INSTITUTIONAL DETAILS

All forest land in India is state property. Hence, if any economic project, such as road or railway construction, canal irrigation, education or medical facilities, mining, etc., requires diversion of forest land, the agency implementing the project needs to get approval from the government. The Forest Conservation Act passed in 1980 set up the institutional framework and rules guiding the approval process. The Act and the subsequent rules specify the primary approving authority depending on project size. All applications for approval are made to the relevant ministry of the State government, which verifies the application details and assesses the project quality before forwarding it to a Regional Office located in various state capitals. For very small projects, with size below 5 hectares, the decisions are made by a high level bureaucrat in the Regional Office.

For years prior to 2004, projects above 5 hectares and up to 20 hectares were decided by a committee in the Regional Office consisting of officials and representatives of the State government. For projects above 20 hectares, the State government directly sent the applications to the Ministry of Environment and Forests of the Central government for approval. In the pre-2004 period, therefore, the State government were the effective approving authority for the projects with size between 5-20 hectares, while projects larger than 20 hectares were decided by the Central government. In 2004, an amendment to the Act

Figure 1—Approving Authority as a Function of Project Size



was proposed, which increased the threshold to 40 hectares. Therefore, the approving authority for these 'mid-sized' projects, i.e., those with between 20-40 hectares changed from the Central to the State government in the post-2004 period. We summarize the rules and their amendment in Figure 1.

2.2 DATA

We compile project-level data on the universe of projects involving the diversion of forest land submitted for government approval in India during the period 1980-2019. The data are available from the website of the Ministry of Environment, Forest and Climate Change (MEFCC), Government of India. The data allow us to extract various details pertaining to each proposal, such as the area of land to be diverted (i.e., project size), its location (state and district), economic purpose of project, date of application and various stages of the approval process and final decision.

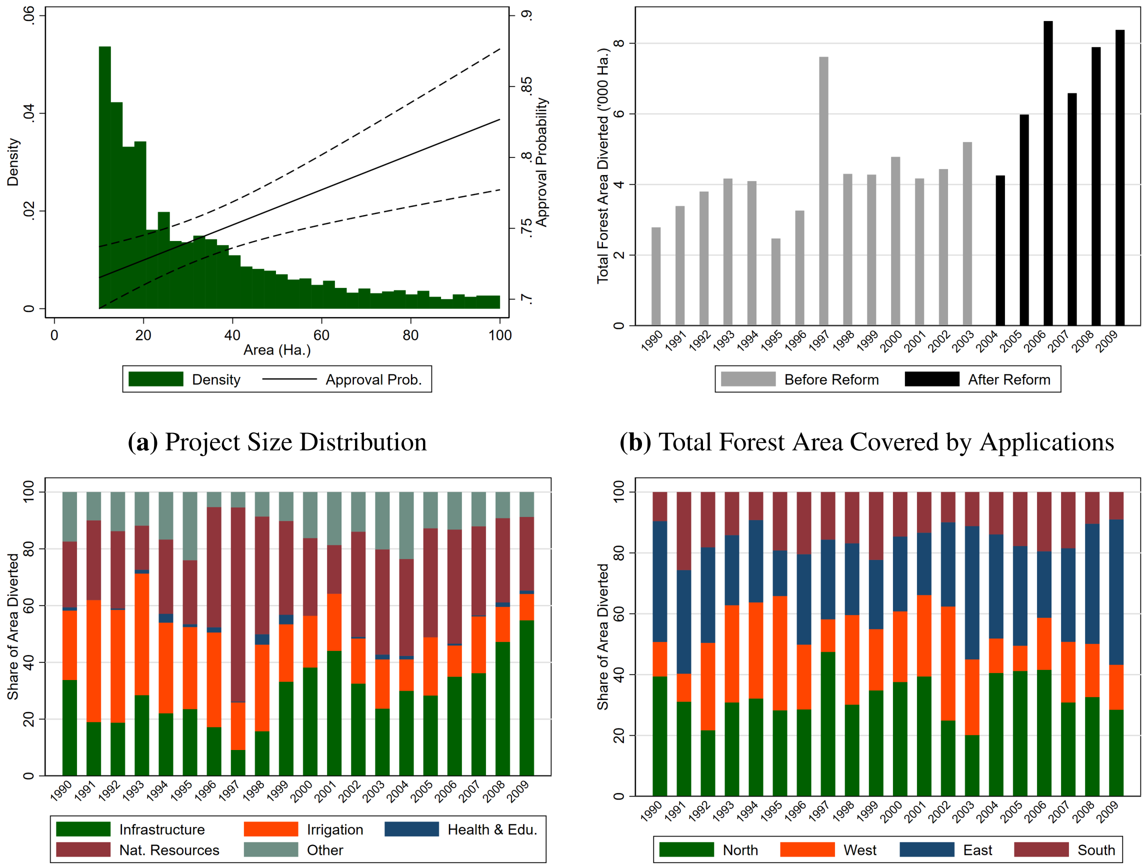
For our analysis, we focus on applications received during 1990-2009 with size in the range of 10-100 hectares. We ignore projects prior to 1990 because the rules and practices guiding the implementation of the Forest Conservation Act did not consolidate in the initial years. Moreover, the establishment of the National Green Tribunal in 2010 allowed citizens to challenge any decision made by the government regarding forest conversion. Since this could potentially impact the application and approval decisions (differentially by the Central and State governments), we do not consider projects after 2010 either. As Section 2.1 describes, projects below 5 Ha. were decided by a single bureaucrat. As shown in Figure A3, there is a significant discontinuity at this threshold that is unrelated to the policy of interest in this paper. Therefore, we ignore the very small projects (below 10 Ha.). Moreover, for projects above 100 Ha., the application process is different requiring more paperwork and inspections. Hence, we restrict our attention to projects between 10 Ha. and 100 Ha..

2.3 DESCRIPTIVE STATISTICS

Our final sample therefore consists of 3108 projects. The average and median project size is 32.3 Ha. and 24.3 Ha. respectively. 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 the total area of forest land that was proposed to be diverted each year. We observe that the amount of forest area proposed to be diverted has increased over the years, especially in the post-2004 period.[4]

[4]Figure A1a in the Appendix shows a similar pattern with the total number of applications as well.

Figure 2—Summary Characteristics of Project Applications



(a) Project Size Distribution

(b) Total Forest Area Covered by Applications

(c) Types of Projects

(d) Project Across Regions

Notes: Figure (a) shows the distribution of projects across the entire sample. Figure (b) shows the total forest area that is proposed to be deforested across all applications in each year. Figures (c) and (d) then show the fraction of this area across different project categories and regions.

Across Project Categories: We categorize projects into 5 categories - infrastructure, irrigation, health and education, natural resources, and others. Infrastructure projects (such as roads, railways, transmission lines, etc.), irrigation projects (such as canals), projects related to energy generation (hydel, thermal, wind, etc.) and mining (natural resources) account for around 85 percent the total number of applications (Figure A1b) and forest area (Figure 2c) covered under them.[5] Medical and education facilities account for around 1 percent of the applications and area covered, while the rest (13 percent) are categorized into an "other" category because no specific economic purpose was mentioned for these projects in the data. As can be seen from these figures, irrigation projects dominated the earlier years in the sample, while infrastructure projects constitute the majority in the latter years.

Across Regions: Similar to the above exercise, Figures 2d and A1c examine the distribution of these projects across different regions of the country over time.[6] These patterns remain fairly stable over the years, with the Northern states accounting for 36 percent of the projects and 34 percent of the forest

[5]More specifically, infrastructure and irrigation projects account for 35.3 and 21.5 percent of the total number of applications, and 32 and 21 percent of the total area proposed under these projects respectively. Mining and energy generation projects constitute 28.7 percent of applied projects and 34 percent of the area covered.

[6]Table A1 provides a classification of Indian states into regions.

area, followed by the Eastern states (around 30 percent of applications and area), Western states (around 20 percent or applications and area), and Southern states (15 percent of projects and area).

Probability of Approval: Figure 2a right hand y-axis shows the probability of approval as a function of project size. Around two-thirds of the projects (64.7 percent to be exact) are approved on average. The approval probability is increasing in size, going from about 70 percent for smallest projects in the sample to about 85 percent for the largest. The probability ranges from 60-70 percent across years. While infrastructure-related projects are more likely to be approved (76 percent), and projects that do not have a specific stated purpose are least likely to be approved (50 percent), there are otherwise no substantial differences in the approval probability either across project categories or regions (Figure A5).

3 REDUCED FORM RESULTS

In this section, we establish certain empirical facts about the approval process under the Central and State governments by exploiting the policy change described in Section 2.1. This will help us motivate the model and the subsequent analysis.

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 for "middle" projects, it changed from the Center to State after the policy reform in 2004.

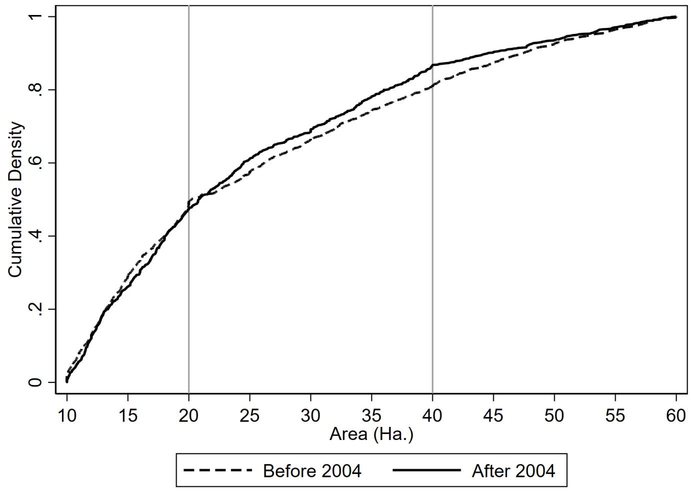
3.1 Volume of Applications

We first examine how the change in approval authority (from Center to State) for the mid-sized projects impacts the applications that they receive. We do so in two ways. First, Figure 3 pools across all projects in the pre- and post-policy period i.e., before and after 2004, and reports the CDF of projects by their size. We see a clear increase in the density of projects between 20-40 Ha. when the approving authority moves from the Center to State governments. We formalize this by estimating a difference-in-differences specification:

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

where Y_{it} is the CDF value for a project i of a category c, located in state s, and applied in year t. $Middle_{it}$ and $Large_{it}$ 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 category and state level, as size of projects could be correlated within broad categories (like infrastructure, irrigation, etc.) as well as across states.

Figure 3—Density of Applications by Size Before and After the Policy Reform



Notes: The above figure plots the CDF of the area proposed across all applications before (dash line) and after (solid line) the policy reform. 20 Ha. and 40 Ha., the relevant policy thresholds are denoted by the vertical lines.

Table 1 reports the results. The primary difference between the columns is the inclusion of fixed effects. Specifically, Column (1) estimates Equation (1) with state and project-category fixed effects along with a Post dummy. State and project-category fixed effects capture all observable and unobservable time-invariant differences across states and project-category that could affect the probability of a project being approved. Column (2) then adds year fixed effects that account for all aggregate changes over time that could impact the approval probability. Lastly, in Column (3), we make the specification more stringent by adding state-category fixed effects in addition to the year fixed effects. This controls for all observable and unobservable state-specific (time invariant) differences across project categories that could impact the approval probabilities.

Turning to the results, we see from Column 1 of Table 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 1.5 pp increase in the CDF value for mid-size projects (estimate for β_2), indicating an increase in mid-sized project applications after the policy.[7]

In a second exercise, we examine the sorting of projects across the policy thresholds and in particular, whether projects (endogenously) decide to sort across the policy threshold with a change in the approving authority. Figure 4 shows the density of applications (as reported from McCrary tests) around the policy thresholds of 20 Ha. and 40 Ha. in pre- and post-2004 periods. Note that in the pre-2004 period, all projects up to 20 Ha. were approved by State governments, and those above 20 Ha. were approved by the Center. Consequently, we see a discontinuous fall in the density of applications at 20 Ha. in the pre-2004 period (Figure 4a, p-value = 0.00), implying that State governments received significantly more applicants around the policy threshold as compared to the Center. As one should expect, there is no discontinuity in the application density at 40 Ha. in the pre-period (Figure 4b, p-value: 0.73).

As described earlier, the policy change in 2004 moved the threshold for approval by the Central

[7]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.

Table 1—Density of Applications

	Cumulative Density Value		
	(1)	(2)	(3)
Post	-0.005		
	(0.005)		
Middle	0.353***	0.352***	0.347***
	(0.008)	(0.008)	(0.007)
Large	0.635***	0.634***	0.629***
	(0.008)	(0.009)	(0.008)
Middle × Post	0.015*	0.015*	0.018**
	(0.008)	(0.008)	(0.007)
Large × Post	0.023***	0.024***	0.026***
	(0.007)	(0.008)	(0.006)
Mean|Small,Pre	0.22	0.22	0.22
R2	0.88	0.88	0.89
N	3108	3108	3060
State FE	Yes	Yes	Yes
Category FE	Yes	Yes	No
Year FE	No	Yes	Yes
State x Cat. FE	No	No	Yes

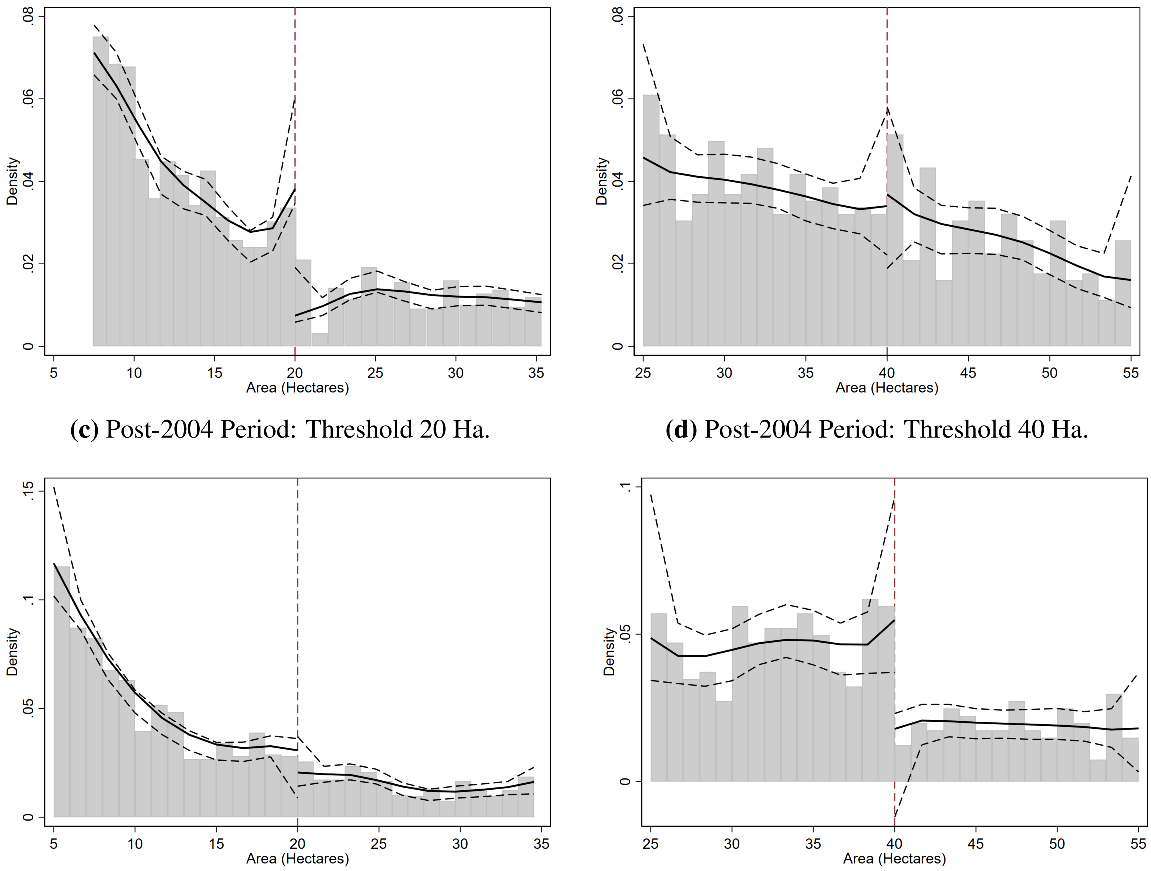
Notes: The dependent variable is the CDF value for the size proposed for each project separately before and after the policy reform. All projects with area 10-100 Ha. are in the sample. The time period is 1990-2009. Middle is a dummy that takes value one if the project area is between 20-40 hectares,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

government from 20 Ha. to 40 Ha. Consequently, we see that the discontinuity in the density of applications also moves to 40 Ha as well in the post-period (Figure 4d, p-value: 0.00) implying that State governments receive more applications than the Center around this threshold. On the contrary, the large discontinuity at 20 Ha. in the pre-period (Figure 4a) no longer exists in the post-period (Figure 4c, p-value: 0.98).

3.2 Average Approval Probability

The previous analysis shows that a shift in the approving authority from Center to State increases the applications that they receive. A potential reason could be that State governments are more likely to approve these applications as compared to the Center. In fact, as we will document below, we find exactly the opposite–State governments are on average *less* likely to approve projects. To examine this, we estimate Equation (1) where the outcome variable a binary variable that takes the value 1 if a project i (in state s and category c) is 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. We cluster standard errors at the project-category and state level, as approval decisions could potentially be correlated across projects within a state or across states within categories.

Figure 4—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.

Similar to Table 1, Columns 1-3 of Table 2 report the results, where we see that a mid-sized project (as compared to a small project) is 8-9 pp (around 12 percent) *less* likely to be approved after the policy reform (i.e., when State governments are the approving authority), as opposed to before it (when these projects were approved by the Center). This is consistent with the finding that β_1 is positive, similar in magnitude and statistically significant at conventional levels i.e., mid-sized projects had a 10 pp higher approval probability under the Central government in the pre-period as compared to smaller projects (under the State government).

Given the discontinuity in the application density around the threshold as discussed above, one may be concerned about the endogenous sorting of projects (by altering the size) across the threshold, which could impact their approval probability as well. To allay this concern, we re-estimate Equation (1) after excluding projects in a 5 Ha. range around these thresholds i.e., we exclude projects in the size intervals $(16, 24)$ Ha. and $(36, 44)$ Ha. As reported in Columns 4-6 of Table 2, the results are quantitatively very similar.[8] Another potential concern could be that the fall in approval probability could happen automatically if the State governments have some form of quota on the aggregate area (or

[8]Since the probability of approval is a binary variable, we re-do the above analysis using a probit model instead and find consistent results, as reported in Appendix Table A4.

Table 2—Approval Rates Before and After the Policy

	1(Project Approved)					
	(1)	(2)	(3)	(4)	(5)	(6)
Post	0.052*			0.072*		
	(0.026)			(0.034)		
Middle	0.101*	0.098*	0.100*	0.095	0.087	0.074
	(0.056)	(0.054)	(0.052)	(0.058)	(0.055)	(0.050)
Large	0.107*	0.106*	0.102*	0.133*	0.127**	0.110*
	(0.058)	(0.057)	(0.054)	(0.062)	(0.059)	(0.056)
Middle × Post	-0.089**	-0.082*	-0.085**	-0.103*	-0.091	-0.080*
	(0.041)	(0.040)	(0.039)	(0.053)	(0.052)	(0.045)
Large × Post	-0.023	-0.021	-0.027	-0.040	-0.032	-0.021
	(0.047)	(0.046)	(0.044)	(0.045)	(0.044)	(0.038)
Mean|Small,Pre	0.67	0.67	0.67	0.67	0.67	0.67
R2	0.07	0.08	0.12	0.08	0.09	0.13
N	3108	3108	3060	2116	2116	2077
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	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. Columns (1) and (4) include state and project category fixed effects. Columns (2) and (5) additionally include year fixed effects and Columns (3) and (6) have state X project category specific fixed effects along with year fixed effects. Standard errors are clustered at the state and project categories and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

number of applications) that they wish to approve in a year. With higher volume of applications, this would mechanically imply lower approval probability. In Appendix Figures A2a and A2b we plot the total number of approved applications and approved area every year. We observe that they both exhibit sharp increase in the post 2004 period mimicking the patterns in total application count and area (Figures A1a and 2b). Therefore, it is unlikely that that State governments follow any quota rule.

3.3 Heterogeneity in Approval Probability

We now show that the change in approval probability induced by the switch in the approval authority depends on the local characteristics of the project's location. While a lower application cost under the State can explain the two results above, heterogeneity in the change in the approval probability based on project location may indicate different preferences across Center and State.

We examine heterogeneity along two dimensions – baseline forest cover and baseline economic development of the districts proxied by nightlight. In the first exercise, we partition the sample into projects located in districts which had higher than median forest cover in the year 2000.[9] We then

[9]That is the first year for which we have forest cover data.

estimate Equation (1) with the approval dummy as the dependent variable for the two samples separately. Table 3 reports the results for the full sample.Appendix Table A2 shows the results for the "restricted sample", i.e., after dropping the projects in the neighborhood of the threshold. We find that for mid-sized projects located in districts with below median forest cover, switching the approval authority *increased* the approval probability (columns (1)-(3)). For projects located in districts with above median forest cover, the average approval probability was lower by about 10 percentage points in the post period. Since the specifications include state and project category fixed effects, the results indicate potentially differential preferences of State vis-a-vis Center in evaluation of projects.

Table 3—Approval Rates and Forest Cover

	1(Project Approved)					
	Below Median			Above Median		
	(1)	(2)	(3)	(4)	(5)	(6)
Post	-0.059**			0.023		
	(0.023)			(0.041)		
Middle	-0.024	-0.016	-0.011	0.098**	0.096*	0.100**
	(0.017)	(0.020)	(0.031)	(0.040)	(0.045)	(0.041)
Large	-0.017	-0.010	-0.001	0.139**	0.140**	0.117**
	(0.064)	(0.062)	(0.066)	(0.056)	(0.057)	(0.046)
Middle × Post	0.060	0.053	0.079**	-0.104***	-0.101***	-0.107***
	(0.042)	(0.035)	(0.026)	(0.018)	(0.021)	(0.022)
Large × Post	0.066	0.058	0.062	-0.073*	-0.070	-0.066
	(0.057)	(0.060)	(0.064)	(0.037)	(0.048)	(0.051)
Mean|Small,Pre	0.82	0.82	0.82	0.75	0.75	0.75
R2	0.06	0.09	0.15	0.07	0.08	0.16
N	1169	1169	1138	1248	1248	1205
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	Whole	Whole	Whole	Whole	Whole	Whole

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. 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 forest cover in a district in the year 2000 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 4 reports the results using district level nighlight as the criteria to partition the sample. Columns (1)-(3) report the results for the sample of projects located in districts with below median nighlight, while Columns (4)-(6) refer to the sample located in above median nightlight districts. We find that approval probability of mid-sized projects located in below median districts decreases by 8 percentage points in the post-period. For mid-sized projects in above median districts, the approval probability on the other hand increases by 6-10 percentage points. Hence, it appears that State is more likely to approve projects located in more developed districts, while less likely to approve those located in less developed districts.

Table 4—Approval Rates and Nightlights

	1(Project Approved)					
	Below Median			Above Median		
	(1)	(2)	(3)	(4)	(5)	(6)
Post	0.013			-0.056		
	(0.013)			(0.041)		
Middle	0.055	0.068	0.067	0.013	0.004	0.006
	(0.056)	(0.058)	(0.055)	(0.027)	(0.030)	(0.037)
Large	0.067	0.078	0.062	0.058	0.053	0.028
	(0.074)	(0.070)	(0.062)	(0.036)	(0.038)	(0.037)
Middle × Post	-0.070*	-0.081**	-0.080*	0.057**	0.072***	0.102**
	(0.035)	(0.036)	(0.039)	(0.020)	(0.017)	(0.038)
Large × Post	-0.023	-0.033	-0.019	-0.008	-0.003	-0.002
	(0.073)	(0.072)	(0.071)	(0.018)	(0.016)	(0.031)
Mean|Small,Pre	0.77	0.77	0.77	0.80	0.80	0.80
R2	0.08	0.09	0.17	0.08	0.10	0.17
N	1263	1263	1214	1154	1154	1123
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	Whole	Whole	Whole	Whole	Whole	Whole

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. 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.

Discussion: Put together, we document that even though State governments have (on average) a lower probability of approving projects, they seem to be getting more applications on average. This suggests that the "quality" of a project could play a key role in rationalizing these patterns, and in particular, State governments could receive worse quality applications of a given size (on average), compared to the Center. The quality of a project denotes the net economic value it will generate for the local area (conditional on its size) and is assessed by local level officials who make inspections of the project site and submit their assessment to the approving authority. The approving authority, therefore, is likely to be aware of project quality, and hence, can condition the approval decision on it. Therefore, even if State governments have a higher approval probability or lower application cost for a project with a given size and quality (which can justify the first observation), its *average* approval probability conditional on size can be lower, due to an adverse selection on the quality of projects.

The empirical facts presented above therefore suggest that either State governments evaluate forest conversion applications differently than the Center, or the application costs are different across them, or both. However, in order to empirically estimate the relative application cost and the relative preference weight that State and Center put on economic development vis-a-vis environmental concerns, we need to model the interaction between the applicants and the government and their decision-making rules.

In what follows, we first build a model of applications and approval decisions (Section 4). This generates an endogenous selection on the quality of projects that choose to apply, conditional on the weight that an approving authority puts on its economic benefit, and the cost of application–both of which vary by the type of government. While sorting is an artefact of the threshold rule, selection is a more general concern with decentralization. So in Section 4, we abstract away from sorting, but bring it in later (Section 8) to estimate the relative importance of sorting vis-a-vis selection in explaining the discontinuity in the application density established in Fact 1.

4 MODEL

A project is indexed along two dimensions (z, 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 approving authority, but not to the researcher. Project (z, S) generates a value $v(z, S) = zq(S)$ where $q(\cdot)$ is strictly increasing and strictly concave in S. The applicant has to decide whether to apply for the project or not. The approving authority (either State or Center), upon receiving the application, decides whether to approve it or not. For now, we do not allow any possibility for an applicant to manipulate the project size to endogenously choose the approving government. While such sorting concerns may be valid for projects near the threshold size, we abstract away from it in our baseline model. In Section 8.2, we augment our model to bring in sorting possibilities and show from the calibration that sorting can explain a small proportion (around 12 percent) of the change in the density of applications that we observe around the threshold in the data.

4.1 Decision of the Government

Consider the payoff of a government (either Center or State) $g \in \{c, r\}$, from approving a project (z, S):

$$U_g(z, S) \ = \ b_g z q(S) - \eta c(S)$$

where b_g is how much government g weights the economic value generated by a project. $c(S)$ is the conservation cost of approving the project i.e., $-c(S)$ is the conversation value of the project. We assume that both governments have the same cost function, which is strictly increasing and weakly convex in S. $\eta \sim F_\eta(\eta)$ is a project-specific idiosyncratic taste (or, preference) shock that a government receives while processing the application. This creates uncertainty about the outcome of the application at the time of seeking approval. b_g captures the relative importance of economic value of a project vis-a-vis forest conservation in government g's payoff. b_g therefore encapsulates the government's development-conservation trade-off and is our parameter of interest. More specifically, a comparison of how b_g changes across Central and State governments would reveal the consequence of decentralization.

The government approves a project as long as $U_g \geq 0$, which implies that the ex-ante approval probability of a project is:

$$P_g(z, S) \ = \ F_\eta\Big[b_g z \phi(S)\Big] \tag{2}$$

where $\phi(x) = \frac{q(x)}{c(x)}$ is the benefit-cost ratio for the government.

Lemma 1 *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., $\partial P/\partial S < 0$.*

See Appendix B.1 for the proof.

Before proceeding, we offer two remarks: first, a project can have additional characteristics apart from its size and quality, such as the local economic characteristics of its location, type of project, identity of applicant etc., all of which could affect the decision of the government. Section 3.3 above shows evidence in favor of this. Hence, b_g could potentially depend on those characteristics. In Section 6.4 we show that our estimates of b_g are meaningfully correlated with the relevant characteristics of projects.

Second, in the model, b_g is a fundamental preference parameter. However, it is possible that b_g depends on the current stock of forest in the economy, i.e., how the government has approved projects in the past. Hence, b_g could potentially be endogenous and time varying. Moreover, it could be guided by how the government evaluates the aggregate economic value generated from all approved projects and the aggregate deforestation that results from it. We develop such a dynamic model in Section 8.1 and show that the estimates from the baseline model can also be interpreted the same way in its dynamic version.

4.2 Decision of the Applicant

The applicant's expected payoff from applying to a government g, denoted by $V(z, S)$, is given by:

$$V_g(z,S) \;=\; \underbrace{P_g(z,S)v(z,S)}_{\text{Expected benefit from the project}} \; -\lambda_g c_A(S) \tag{3}$$

where $c_A(S)$ is the application cost incurred by the applicant. $c_A(S)$ is strictly increasing and weakly convex function. λ_g is a cost-shifter of applying to a particular type of government, which is a reduced-form way of capturing differential costs that an applicant might have of applying to either the State or Central government. Given the above structure, an applicant will apply for the project with a government g as long as $V_g(z,S) \geq 0$. Since $\partial V_g(z,S)/\partial z > 0$, it implies that for a given S, there is a threshold $z_g^*(S)$ such that the applicant will apply only if $z \geq z_g^*(S)$, where $z^*(S)$ is determined by:

$$P_g\left[z_g^*, S\right] \times z_g^* \psi(S) = \lambda_g \tag{4}$$

where: $\psi(S) = \frac{q(S)}{c_A(S)}$ and similar to $\phi(S)$, $\psi'(S) < 0$.

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

See Appendix B.2 for the proof. Intuitively, since larger projects (higher S) have a lower probability of being approved and lower benefits (net of costs), they have to be even more productive (higher z) to be proposed. The mass of *applied* projects of size S, denoted by the PDF $\xi_g(S)$, will be the set of projects for $z > z_g^*$ so that:

$$\xi_g(S) \;=\; 1 - F_z(z_g^*(S)) \tag{5}$$

As is evident from the equation, the height of the PDF declines with S since $\partial z_g^*/\partial S > 0$. Lastly, the average approval probability for all applied projects of a given size S is therefore given by:

$$\overline{P}_g(S) = \int_{z \geq z_g^*(S)} P_g(z, S) \frac{dF_z(z)}{1 - F_z(z_g^*(S))} \tag{6}$$

5 MODEL CALIBRATION

5.1 Parameterization

To take the model to the data, we make the following assumptions: (i) we assume that the distribution of project quality follows a Pareto distribution with a shape parameter θ i.e., $z \sim Pareto(\theta)$ i.e., $F_z(z) = 1 - z^{-\theta}$; (ii) we assume that η follows a Uniform distribution on $[0, 1]$ i.e., $F_\eta(\eta) = \eta$.[10] With these distributional assumptions, we can now simplify the above theoretical equations to obtain:

$$\text{Prob. of Approval: } P_g(z, S) = b_g z \phi(S) \qquad \text{(From Equation 2)} \tag{7}$$

$$\text{Threshold quality: } z_g^*(S) = \sqrt{\frac{\lambda_g}{b_g \phi(S) \psi(S)}} \qquad \text{(From Equation 4)} \tag{8}$$

$$\text{PDF of Applied Projects: } \xi_g(S) = (z_g^*)^{-\theta} \qquad \text{(From Equation 5)} \tag{9}$$

$$\text{Avg. Approval Prob.: } \overline{P}_g(S) \equiv E(P_g(z)|S) = \frac{\theta}{\theta - 1} \times \underbrace{b_g z_g^* \phi(S)}_{=P_g(z_g^*, S)} \qquad \text{(From Equation 6)} \tag{10}$$

$$\text{Var. Approval Prob.: } V(P_g(S)) = Var(P_g(z)|S) = \frac{2}{\theta - 2} \overline{P}_g^2 \tag{11}$$

5.2 Identification

As we will discuss below, we are able to identify $b \equiv b_r/b_c$ and $\lambda \equiv \lambda_r/\lambda_c$ i.e., we are able to examine the importance of economic development vis-a-vis conservation in State government's payoff *relative* to the Central government's payoff, and the relative application cost of applying to State government compared to the Center. $b < 1$ would indicates a higher preference by the State government to conserve forests relative to the Center. Given this, note from the above equations that:

$$\lambda = \frac{\overline{P}_r z_r^*}{\overline{P}_c z_c^*} \quad \text{and } b = \frac{\overline{P}_r / z_r^*}{\overline{P}_c / z_c^*} \tag{12}$$

In the ideal case, if we were able to *separately* observe the distribution of applications for *both* the Center and State across the entire size distribution, we would be able to identify b_g and λ_g separately for each g. While this is not possible, our policy change (Section 2.1) provides us with a unique way to identify these parameters as follows: since approval for 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 distribution and outcome of applications to identify λ and b in Equation (12) above.

Turning to the moments that we can observe in the data, note that the average probability of approval $\bar{P}_g$ is directly observable in the data. The ratio z_r^*/z_c^* can be estimated from the size distribution, but

[10] 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 $[0, 1]$.

we cannot simply invert the size distributions to take these ratios from the data since the 'treatment' also confounds a possible time-trend in the application distribution and approval probabilities. To see this, consider two time periods $t = \{0, 1\}$ corresponding with pre and post policy reform periods, respectively. $\overline{P}_g$ and $z^*_g(S)$ can change over time because $\psi(S)$ and $\phi(S)$ can be time varying; this is realistic since the project production and cost functions might change over time.

For a government g, we therefore assume that: $\phi_{g1}(S) = \alpha_g \phi_0(S)$ and $\psi_{g1}(S) = \beta_g \psi_0(S)$.[11] We now take advantage of the policy reform, which was only applicable to $S \in (20, 40)$. To eliminate endogenous sorting across the thresholds, we consider the interval $S \in [25, 35]$. We refer to these projects as MID sized and projects with $S \in [10, 15]$ as SMALL sized. From Equations (8) and (10) we get:

$$\left[\frac{z^*_{r1}}{z^*_{c0}}\right]^{\text{MID}} = \sqrt{\frac{\lambda}{b}} \times \sqrt{\frac{\phi_{c0}\psi_{c0}}{\phi_{r1}\psi_{r1}}} = \underbrace{\sqrt{\frac{\lambda}{b}}}_{=\text{ Policy Impact}} \times \underbrace{\sqrt{\frac{1}{\alpha_r \beta_r}}}_{=\text{ Time Trend}} \tag{13}$$

$$\underbrace{\left[\frac{\overline{P}_1}{\overline{P}_0}\right]^{\text{MID}}}_{\text{Data}} = \frac{\overline{P}_{r1}}{\overline{P}_{c0}} = b \times \frac{z^*_{r1}}{z^*_{c0}} \times \frac{\phi_{r1}}{\phi_{c0}} = \underbrace{\sqrt{b\lambda}}_{=\text{ Policy Impact}} \times \underbrace{\sqrt{\frac{\alpha_r}{\beta_r}}}_{=\text{ Time Trend}} \tag{14}$$

Time Trend: From the above equation, $\{\alpha_r, \beta_r\}$ denote the changes in the $\{\phi, \psi\}$ functions for the state government between the two time periods. We take advantage of the fact that the approval decisions for applications under 20 Ha. were always under the State government in both the pre- and post-period to calculate these. Specifically, we consider the probability of approval and empirical distribution of applications for $S \in [10, 15]$ Ha. (to mitigate concerns from sorting between 15-20 Ha. projects) and note that:

$$\left[\frac{z^*_{r1}}{z^*_{r0}}\right]^{\text{SMALL}} = \sqrt{\frac{\phi_{r0}\psi_{r0}}{\phi_{r1}\psi_{r1}}} = \sqrt{\frac{1}{\alpha_r \beta_r}} \tag{15}$$

$$\underbrace{\left[\frac{\overline{P}_1}{\overline{P}_0}\right]^{\text{SMALL}}}_{\text{Data}} = \frac{\overline{P}_{r1}}{\overline{P}_{r0}} = \frac{z^*_{r1}}{z^*_{r0}} \times \frac{\phi_{r1}}{\phi_{r0}} = \sqrt{\frac{\alpha_r}{\beta_r}} \tag{16}$$

Estimating z^*_g: To estimate 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 $\xi_1(S)$, respectively, which we observe in the data. Specifically from Equations (8) and (9):

$$\xi_0(S) = \frac{z^*_{g0}(S)^{-\theta}}{\int_{10}^{20} z^*_{r0}(S)^{-\theta} dS + \int_{20}^{100} z^*_{c0}(S)^{-\theta} dS} \qquad \text{where } g = r \text{ if } S \in [10, 20]$$

$$\text{and } g = c \text{ if } S \in (20, 100]$$

[11] Note that in theory, *both* the initial level of $\{\psi(S), \phi(S)\}$ as well as their change over time $\{\alpha, \beta\}$ 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.

$$\xi_1(S) = \frac{z^*_{g1}(S)^{-\theta}}{\int_{10}^{40} z^*_{r1}(S)^{-\theta} dS + \int_{40}^{100} z^*_{c1}(S)^{-\theta} dS} \qquad \text{where } g = r \text{ if } S \in [10, 40]$$

$$\text{and } g = c \text{ if } S \in (40, 100]$$

Henc define:

$$\chi_0 \equiv \underbrace{\left\{ \frac{\xi_0^{\text{MID}}}{\xi_0^{\text{SMALL}}} \right\}^{-\frac{1}{\theta}}}_{\text{Data}} = \frac{z^{*\ \text{MID}}_{c0}}{z^{*\ \text{SMALL}}_{r0}} \quad \text{and} \quad \chi_1 \equiv \underbrace{\left\{ \frac{\xi_1^{\text{MID}}}{\xi_1^{\text{SMALL}}} \right\}^{-\frac{1}{\theta}}}_{\text{Data}} = \frac{z^{*\ \text{MID}}_{r1}}{z^{*\ \text{SMALL}}_{r1}} \tag{17}$$

which gives us:

$$\underbrace{\frac{\chi_1}{\chi_0}}_{\text{Data}} = \left[\frac{z^*_{r1}}{z^*_{c0}} \right]^{\text{MID}} \times \left[\frac{z^*_{r0}}{z^*_{r1}} \right]^{\text{SMALL}} \tag{18}$$

Identifying λ and b: Denote $\mathcal{P}^X = \left[\frac{\overline{P}_1}{\overline{P}_0} \right]^{\text{X}}$ for $X = \text{SMALL, MID}$. Substituting Equations (13) and (15) in (18) and (16) in (14), we get:

$$\underbrace{\frac{\chi_1}{\chi_0}}_{\text{Data}} = \sqrt{\frac{\lambda}{b}} \qquad \text{and} \qquad \underbrace{\frac{\mathcal{P}^{\text{MID}}}{\mathcal{P}^{\text{SMALL}}}}_{\text{Data}} = \sqrt{b\lambda}$$

$$\Rightarrow b = \frac{\mathcal{P}^{\text{MID}}}{\mathcal{P}^{\text{SMALL}}} \times \frac{\chi_0}{\chi_1} \qquad \text{and} \qquad \lambda = \frac{\mathcal{P}^{\text{MID}}}{\mathcal{P}^{\text{SMALL}}} \times \frac{\chi_1}{\chi_0} \tag{19}$$

5.3 Parameter Calibration

Table 5—Values of (θ, b, λ) Based on Different Sample Restrictions

Sample	θ	b	λ	$\sqrt{\lambda/b}$	$\sqrt{b\lambda}$
	(1)	(2)	(3)	(4)	(5)
Whole Sample, Both	5.33	0.9434	0.8880	0.9702	0.9153
Whole Sample, Pre-Period	5.59	0.9420	0.8893	0.9716	0.9153
Whole Sample, Post-Period	5.31	0.9435	0.8879	0.9701	0.9153
Restricted, Both	5.33	0.9434	0.8880	0.9702	0.9153
Restricted, Pre-Period	5.44	0.9428	0.8886	0.9708	0.9153
Restricted, Post-Period	5.31	0.9435	0.8879	0.9701	0.9153
Whole Sample, Both	5.33	0.9434	0.8880	0.9702	0.9153

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 15-45 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.

Given the above discussion and identification, we now turn to estimating the three parameters of interest, namely: $\{\theta, b, \lambda\}$. Our empirical calibration will closely follow generating the empirical counterparts to Equations (8)-(11). We proceed as follows: first, we pool all projects in the pre- and post-reform period and for each size S, calculate the empirical density and the average and variance of the approval probability. To gain precision (since S is a continuous distribution) we discretize S in levels of 1 Ha.

STEP 1. Re-arranging Equation (11), $\hat{\theta} = 2(1 + \overline{P}_g^2/V(P_g))$. Note that since the RHS of the above equation is observable in the data for each project size S, the above exercise gives us a $\hat{\theta}$ for each S. Our preferred value of θ is the median value of $\hat{\theta}(= 5.33)$ in the entire sample. However, in Table 5, we report the values across various other sub-samples in the data, which range from 5.31-5.59.

STEP 2. Given $\hat{\theta}$ and the empirical density at size S i.e., $\xi(S)$, we can obtain $(\xi(S))^{-1/\hat{\theta}}$.

STEP 3. Given $(\xi(S))^{-1/\hat{\theta}}$ and $\overline{P}(S)$ for both the pre- and post-periods, we average over the size distribution in $X = \{\text{SMALL,MID}\}$ and then calculate the ratios χ_1/χ_0 and $\mathcal{P}^{\text{X}}$ defined previously. Substituting them in Equation (19), we get $b = 0.94$ and $\lambda = 0.89$. As reported Table 5, these values are robust to alternative sub-samples and the corresponding parameter values of θ.

6 MODEL VALIDATION

In this section, we provide four independent checks to incrase our confidence in the calibration exercise discussed above, as well as the resulting parameter estimates. First, in Section 6.1, we compare the impact of the policy from the model estimates to the reduced form results from Section 3 and find that they are very close to each other.

Second, our model predicts that State governments receive more applications, and applications of lower quality. While Figure 4 directly supports the former, we provide additional support in Section 6.2 by showing that the time taken to evaluate applications in the 20-40 Ha. range systematically increase by around 15-20 percent once the approving authority changes from the Center to the State.

Third, we directly measure a proxy for the quality of the project. Application data after 2014 also reports the total employment expected to be generated from a project. In Section 6.3, we use these data to create a measure of the minimum threshold quality of a project that proxies for z^* in our model, and show that it systematically varies across the policy threshold in line with the prediction of the model.

Lastly, in Section 6.4, we examine whether our parameter estimates vary systematically with the underlying socio-political conditions in those areas. For example, we find that areas that have an above-median forest cover also have a higher preference for forest conservation (lower b). Similarly, application costs are lower for projects proposed in those districts that are either in the same district as the Regional Office, or when the political parties in the state and center are aligned.

6.1 Validation from the Difference-in-Differences Regression

From the model, note that the percentage change in the average probability of approving mid-sized projects with a change in the approving authority, i.e., the impact of the policy reform, is given by $\sqrt{b\lambda} - 1$. From Table 2, we can also write this as $\hat{\beta}_2/E(P_{i0}|\text{Mid, Before 2004})$. Substituting in the values from Column 3, this is equal to -0.085/0.77 = -0.11. In general across Columns 1-6, this value varies from -0.106 to -0.135, which implies a $\sqrt{b\lambda}$ ranging from of 0.87-0.89 and is very comparable to the model estimate of 0.91 in Column 5 of Table 5.

6.2 Time Taken for Approval Decision

For each project in our data, we can measure the number of days taken for the approving authority to make a decision on the project. In particular, there are two stages of approval, namely Stage 1 and Stage 2. We therefore 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 A5 and A6 for Stage 1 and Stage 2 respectively. We see that in the pre-period (before 2004), projects under 20 Ha. (Small) took on average 615 days to receive their Stage 1 approval, and around 1075 days for their Stage 2 approval. As with the earlier analysis, our coefficient of interest is Middle$\times$ Post, which reports the change in the time taken to approve projects between 20-40 Ha. (relative to those under 20 Ha.) when the approving authority changes from the Center to the State,

Turning to the results, first, it is important to note that the decision time for the set of applications that were always approved by either the State or Center (i.e., the Post and Large$\times$Post coefficients) reduces substantially before and after 2004, by around 185-210 days (30-33 percent) for Stage 1, and 250-270 days (23-25 percent) for Stage 2. On the contrary, we see robustly (across various specification and sample restrictions) that the decision time for the applications between 20-40 Ha. (relative to under 20 Ha.) between the pre and post 2004 periods actually increased, by 90-120 days (15-20 percent) for Stage 1 and 130-180 days (13-17 percent) for Stage 2. This is consistent with the implications of our model where State governments receive more applications and applications of lower quality.

6.3 Quality of Projects Received Across Governments

The analysis so far suggests that while State governments get more applications, they are also of lower quality. While the first statement (more applications) is directly measured in Figure 4, we do not have a direct measure for project quality. To make progress, we use the fact that applications for each project after 2014 also ask applicants to report the total employment that would be generated from a project if it were to be approved. Using this measure, we calculate, for each size S, the minimum (log) employment generated across all applications during 2014-2019.[12] Through the lens of our model, this would correspond to a measure of $z^*(S)$.[13] Our model predicts that $z^*(S)$ is increasing in S for a given government, and is lower for applications received by the state government. We plot minimum log employment against S around the size threshold of 40 Ha. We therefore expect a discontinuously higher value of minimum log employment at the size threshold of 40 Ha.

As reported in Figure 5a, we find that the minimum (log) employment generated is both lower on average as well as at the 40 Ha. discontinuity, 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). Table A8 formalizes this and reports the coefficient at the discontinuity in the minimum quality (Column 1) as well as the 1-3 percentiles (Columns 2-4). All coefficients are positive in magnitude (as expected) and statistically significant at conventional levels. In both cases, the graph is generally upward sloping, which is consistent with our model. For project between 30-40 Ha., the minimum log employment appears to fall with S. This is likely due to sorting of lower quality projects

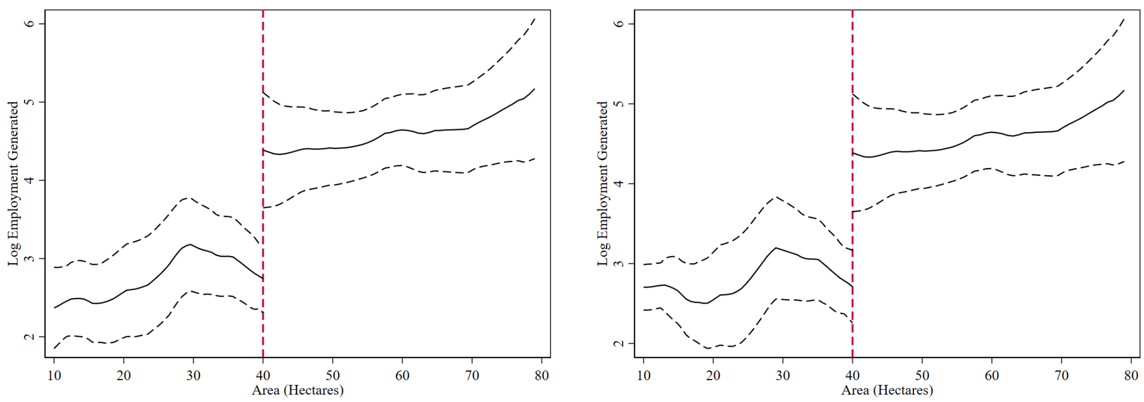
[12] We discretize the size into bins of 1 Ha.

[13] As a check for consistency, we show that the density of applications received in the 2014-19 period (Figure A5) also exhibits the same discontinuity that we observe in the 2004-09 period (Figure 4). 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).

into the left of the threshold. We discuss this formally in Section 8.2.

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 the employment generated by the project on the vertical axis. All projects proposed between 2014-2021 with area between 10-80 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. The dotted lines denote the 95th percentile confidence intervals.

Put together, both the above observations support the hypothesis that State governments did receive applications of lower quality after the change in the policy.

6.4 Correlation of Parameter Estimates with Economic and Political Factors

In this section, we examine whether pre-existing economic and other conditions influence the parameters b and λ. The parameters in the model are a reduced form way for us to capture governments' preferences and agencies' application costs. By testing whether the parameter estimates respond meaningfully to changes in the factors that can potentially affect the preferences and costs, we would be able to interpret the estimates better. For this purpose, we focus on two factors that directly affect the preferences of governments – namely, the intensity of citizens' preferences for conservation, proxied by the baseline forest cover in the project's district, and the existing level of development in the project's district. We further examine two additional factors that potentially affect the relative cost of application – namely, whether Regional office is located in the state capital and whether the Center and State are politically aligned (i.e., have the same political party in power).

Forest Cover: We first investigate whether projects originating from districts that have a stronger preference for conservation are associated with differential evaluation by the central and state governments. We argue that district level forest cover is a good proxy of the preference of district population for forest conservation. We use VCF data to compute percentage of land area in a district having forest cover. We match this district level measure for 2005 to the Rural Economic and Demographic Survey of 2006 that asks individuals about their preferences for various public goods including forest conservation. Appendix Table A7 shows that district level forest cover is a strong predictor of rural residents of the districts having a stronger preference for forest conservation. We therefore estimate the parameters of our model on two sub-samples of applications - those in districts with above median forest cover in year 2000 and those in below median districts. The first row of Table 6 reports the estimates of b

Table 6—Estimation of b and λ in Sub-samples

	b	λ	b	λ
	(1)	(2)	(3)	(4)
	Below Median		Above Median	
Forest Cover	**1.24**	0.95	**0.83**	0.95
Nightlights	**1.04**	0.97	**0.98**	0.96
	Absent		Present	
Regional Office	1.17	**1.02**	0.83	**0.86**
Political Alignment	1.10	**1.05**	0.80	**0.76**

Notes: Above Median refers to projects' districts having higher than median value in year 2000.

and λ for below and above median districts, respectively. Both samples produce similar estimates of λ. This is expected as projects in districts with greater forest cover should not have lower application costs. However, the estimates of b are significantly different across the samples. Its value is 1.24 in districts with lower forest cover and 0.83 in districts with higher forest cover. Therefore, greater presence of forests (and hence, stronger preference for conservation among citizens) increases the relative value of conservation more for the states than center. Hence, stronger citizen preference for conservation can make decentralization more beneficial for conservation.

Nightlights: We similarly estimate b and λ separately on sub-samples of applications located in districts with higher and lower than median nightlights in the year 2000. As before, we find that the estimates of λ are similar. However, the estimate of b in the less developed districts is 1.04, while it is 0.98 in the more developed districts. It implies that projects originating in less developed districts are more valuable to the state than the center. This could be because the electoral gain from improving the economic condition of a district's local economy (by approving a project) is higher for the state than the center. Therefore, decentralization leads to faster deforestation in less developed areas.

Regional Office Presence: If the Regional Office is located in the state capital, it can potentially affect the application cost to the state, as the applicant is more likely to have a better idea about the priorities of the officials in the Regional Office due to physical proximity. We estimate the parameters for two sub-samples – applications located in state with and without Regional Offices. The estimates are in the third row of Table 6. We find that estimate of λ is significantly lower than one (0.86) for applications located in states with Regional Office, while it is 1.02 for the other applications. Therefore, in those states applicants prefer to apply to the center than to the state. Hence, physical proximity to the decision maker is an important driver of application cost. Decentralization therefore can worsen the adverse selection of projects by reducing application cost.

Political Alignment: We examine whether political alignment between the center and the state governments affect the application cost. If political connections matter for application, then having the same political party in power at both levels can make the application process significantly easier, especially for the applicants with ties to the party in power. Table 6 row 4 shows that for projects originating in political aligned state-year pairs, estimate of λ is 0.76, while for other projects it is 1.05. Therefore, political ties can also worsen the adverse selection problem associated with decentralization.

7 IMPACT OF DECENTRALIZATION

The above exercise now provides us with the necessary information to understand the impact of decentralization. In particular, there are three channels through which this impact can be measured, the first two being more general, and the last one (sorting) being an artifact of the threshold nature of the decentralization policy. The first channel is the change in the probability of approval *conditional* on application, which from Equation (7), is simply b. This implies (from the calibration above) that conditional on applying, the probability of approval actually decreased by 5.6% i.e., State governments actually prefer forest conservation as compared to the Center.

A second channel speaks to the lower cost of application, λ, that along with b, drives the selection of projects that now make applications. Table 5 shows that λ is 0.89, i.e., cost of application is 11% lower under State government as compared to the Center. Therefore, even with a lower approval probability conditional on applying (lower b), the overall selection effect can be measured by the increase in the mass of mid-sized projects that now apply to the State that otherwise would not have applied under the Center. This is given by $(\sqrt{\lambda/b})^{-\theta} = 1.18$, which implies that 18% more projects that would not have been applied under the Central government regime, now apply under the State governments. The selection effect, therefore, attenuates the direct positive effect of decentralization on conservation. Put together (as implied in Equation (14)), the average probability of approvals (measured by $\sqrt{b\lambda}$) is now 0.92 or 8% lower after the policy reform. Coupled with a 18% increase in application volume, it implies a net 8.6% $(= (0.92 \times 1.18) - 1)$ *increase* in deforestation due to decentralization.

We examine these effects directly by compiling a district level panel data comprising of percentage of forest coverage (available from VCF dataset) and nightlights (available from NOAA).[14] We estimate the following regression:

$$Y_{dst} = \phi_d + \phi_{st} + \delta_M M_{ds} * Post_t + \delta_L L_{ds} * post_t + \epsilon_{dst} \tag{20}$$

where Y_{dst} is log of nightlights or log of forest coverage in district d in state s in year t, $post_t$ is a dummy indicating the post-2004 period and M_{ds} is either the fraction of application from district d which are of "middle" size, i.e., 21-40 Ha. in the year 1990 or a dummy variable indicating whether any application of "middle" size was received from district d in year 1990. L_{ds} is a similar pair of variables defined for "large" sized projects, i.e., 41-100 Ha. ϕ_d and ψ_{st} are district and state-year fixed effects. The coefficient of interest is δ_M that measures whether nightlights and forest cover changed differentially in the post period for the districts having more (or any) mid-sized projects. Districts that received more mid-sized projects at the baseline were, in some sense, more exposed to the decentralization reform in

[14] We source the outcome variables from SHRUG data verse. The VCF data covers the time period from 2000-2009, while the nightlights data is available from 1994-2009.

Table 7—Night Lights and Forest Cover in a District

	Ln(Investment)	Ln(Night Lights)
	(1)	(2)
Above Med. Medium App. $\times$ Post	-0.145	-0.052***
	(0.152)	(0.011)
R2	0.67	0.97
N	2037	5028
District FE	Yes	Yes
State x Year FE	Yes	Yes

Notes: The outcome variables are the log-Night Lights and Forest Cover in a district d in a year t, which are obtained from the SHRUG data. Night Lights data is available from 1994-2009, while the Forest Cover data is available from 2000-2009. Frac. Medium App. are the fraction of applications in the 21-40 Ha. (Medium) category in the pre-policy period. Above Med. Medium App. takes the value 1 if that district had above median fraction of applications in the medium category in the pre-policy period. Post takes the value 1 for years after 2004 and 0 otherwise. All regressions control for district and state-year fixed effects. Robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

the post-2004 period. Therefore, δ_M estimates the effect of decentralization on the outcome variables.

Table 7 reports the results. We find that the estimate of δ_M is negative and statistically significant for nightlights for both measures of M_{ds} (Columns 1 and 2). This is consistent with the analysis above that argued that decentralization led to lower quality of economic projects being implemented. Columns 3 and 4 show that the estimate for forest coverage is also negative but not statistically insignificant. This implies that the decentralization did not result in any dramatic increase in deforestation. This is reasonable given our finding that decentralization resulted in more deforestation as a net outcome of two opposing forces – lower approval of projects as well as more number of applications, with the latter dominating.

8 Extensions of the Model

8.1 A Dynamic Model of Deforestation

In the model described in Section 4, the government evaluates each project separately using its preference parameter b_g. However, the government's value of a project may depend on the other projects it has approved and the existing stock of forest, i.e., it could be *endogenous*. In this extension, we consider an infinite period model where in every period t, applicants apply with projects (z, S) and governments make approval decisions on the applied projects as described in Section 4. However, unlike in the static model, the government optimally *chooses* b_g every period to maximize its life-time payoff in this case. We describe the components of the model and its detailed timeline and payoff functions of the entities below.

There are infinite periods, denoted by $t = \{0, 1, 2, \dots\}$. The economy begins with a stock of forest resource R_0 in period $t = 0$. There is a government g that lives for infinite periods. Applicants are born with a project each with characteristics (z, S), where $z \sim F_z(z)$ is drawn independently of S.

An applicant lives for only one period and care about the expected payoff from one application. The applicant therefore either chooses to apply with the project he is born with or does not apply and gets payoff zero.[15]

Timeline within each period:

1. At the beginning of every period t, government chooses b_{gt}.
2. Applicants with projects (z_t, S_t) observe b_{gt} and decide whether to apply, given application cost $\lambda_g c_A(S_t)$.
3. Project specific shocks η_t are realized. $\eta_t \sim F_\eta(\cdot)$ for all t.
4. Government approves a project if and only if

$$b_{gt} z_t q(S_t) \geq \eta_t c_0 S_t$$

where $z_t q(S_t)$ is the value of the project and $c_0 S_t$ is the cost of deforestation, which is assumed to be linear with $c_0 > 0$ as some constant. Hence c_0 is the marginal value of forest.

Payoffs: Applicant's payoff from applying with project (z, S) in period t is:

$$B_t = P_g(z, S, b_{gt}) z v(S) - \lambda_g c_A(S)$$

where λ_g is the exogenously specified government specific cost shifter, as before. $P_g(z, S, b_{gt})$ is the probability of approval, given by

$$P_g(z, S, b_{gt}) \ = \ F_\eta\left(b_{gt} z \phi(S)\right)$$

The government is long-lived and its lifetime payoff is given by

$$\Pi_g(R_0) = \sum_{t=0}^{\infty} \delta^t \left\{\omega_g V_t + c_0(R_t - D_t)\right\} \tag{21}$$

where δ is the discount factor, V_t is the aggregate value generated from all the approved projects in t, D_t is the aggregate deforestation in t, R_t is the stock of forests at the beginning of period t. Hence $c_0(R_t - D_t)$ is the flow payoff from remaining stock of forest. ω_g is government's fundamental preference weight on economic development vis-a-vis forest conservation. For any choice of b_{gt} in any period t, D_t is given by

$$D_t \ = \ \int_S \int_{z \geq z_g^*(S)} S P_g(z, S, b_{gt}) dF_z(z) dF_{R_t}(S) \tag{22}$$

[15] Making the applicant long-lived may introduce an incentive for some applicants to strategically delay application. This will substantially increase the complexity of the model. The current model delivers the main insight from this exercise without entertaining this additional complexity.

where $z_g^*(S)$ is as defined in Section 4 and $F_R(\cdot)$ is the size distribution of all potential projects that can be applied given the stock of forest R. Similarly, V_t is given by

$$V_t = \int_S \int_{z \geq z_g^*(S)} zq(S)P_g(z, S, b_{gt})dF_z(z)dF_{R_t}(S) \tag{23}$$

The optimization problem for the government g is therefore

$$\begin{aligned} \max_{\{b_{gt}\}} \Pi_g(R_0) &= \max_{\{b_{gt}\}} \sum_{t=0}^{\infty} \delta^t \{\omega_g V_t + c_0(R_t - D_t)\} \\ \text{sub. to } R_{t+1} &= R_t - D_t \end{aligned} \tag{24}$$

given equations (22) and (23).

8.1.1 Solution

Solving the optimization problem above without any additional structure is difficult. We assume, as before, that $\eta_t \sim Uniform[0,1]$ and $z \sim Pareto(\theta)$. Hence, we get that

$$D_t = b_{gt}^{\frac{1+\theta}{2}} \lambda_g^{\frac{1-\theta}{2}} \Gamma_D(R_t), \text{ and}$$

$$V_t = b_{gt}^{\frac{\theta}{2}} \lambda_g^{1-\frac{\theta}{2}} \Gamma_V(R_t)$$

$$\text{where } \Gamma_D(R_t) = \frac{\theta}{\theta - 1} \int_S S\phi(S)^{\frac{\theta+1}{2}} \psi(S)^{\frac{\theta-1}{2}} dF_{R_t}(S) \text{ and}$$

$$\Gamma_V(R_t) = \frac{\theta}{\theta - 2} \int_S q(S)\phi(S)^{\frac{\theta}{2}} \psi(S)^{\frac{\theta}{2}-1} dF_{R_t}(S)$$

Let $\{b_{gt}^*\}$ be the solution to (24). We then have the following result:

Proposition 3 *The optimal solution is given by:*

$$b_{gt}^* = \omega_g^2 \lambda_g \kappa(R_t) \quad \textit{where } \kappa(R) = \left[\frac{\theta}{\theta+1} \frac{1-\delta}{c_0} \frac{\Gamma_V(R)}{\Gamma_D(R)}\right]^2$$

See Appendix Section B.4 for proof.

The result above describes how b_{gt}^* evolves over time as R_t changes. The optimal path exhibits certain expected characteristics. For example, as c_0 increases, b_{gt}^* decreases for all t. This is because higher c_0 implies higher cost of deforestation, which makes the government put a lower weight on the value of any given project during the approval process. Similarly, a more patient government (i.e., higher δ) chooses lower b_{gt}^* as the stock of forest has higher continuation payoff when patience is higher. Understandably, b_{gt}^* is increasing in ω_g. Interestingly, the function $\kappa(R_t)$ is independent of the type of government. Hence, the paths of b_{gt}^* across central and regional governments are proportional to each other. Therefore, even though b_{gt}^* changes over time for any government g, $b_t^* = b_{rt}^*/b_{ct}^*$ is *constant* and hence, can potentially be estimated for a sample.

Let $b^* = b^*_{rt}/b^*_{ct}$, $\lambda = \lambda_r/\lambda_c$ and $\omega = \omega_r/\omega_c$. Then Proposition 3 implies that

$$\omega = \sqrt{\frac{b^*}{\lambda}} \tag{25}$$

We therefore get that the fundamental preference parameter ω can be expressed as the square root of the ratio of b and λ. In other words, we can interpret the preference weight of a long-lived government as square root its *project level* preference weight relative to its application cost parameter. Since we are able to identify both b and λ in the static model, we can identify ω in this dynamic model as well.

8.1.2 Identification and Calibration

We follow the identification method described in Section 5.2 and compute the following:

$$\mathcal{P}^{MID} = \frac{\overline{P}_{r1}}{\overline{P}_{c0}} = \sqrt{\lambda \times \frac{b^*_{r1}}{b^*_{c0}}} \times \sqrt{\frac{\alpha_r}{\beta_r}}$$

$$\begin{aligned} \mathcal{P}^{SMALL} &= \frac{\overline{P}_{r1}}{\overline{P}_{r0}} = \sqrt{\frac{b^*_{r1}}{b^*_{r0}}} \times \sqrt{\frac{\alpha_r}{\beta_r}} \\ \Rightarrow \quad \frac{\mathcal{P}^{MID}}{\mathcal{P}^{SMALL}} &= \sqrt{\lambda \times \frac{b^*_{r1}}{b^*_{c0}}} \times \sqrt{\frac{b^*_{r0}}{b^*_{r1}}} = \sqrt{b^* \lambda} \end{aligned} \tag{26}$$

Similarly,

$$\begin{aligned} \left[\frac{z^*_{r1}}{z^*_{c0}}\right]^{\text{MID}} &= \sqrt{\lambda \times \frac{b^*_{c0}}{b^*_{r1}}} \times \sqrt{\frac{1}{\alpha_r \beta_r}} \\ \left[\frac{z^*_{r1}}{z^*_{r0}}\right]^{\text{SMALL}} &= \sqrt{\frac{b^*_{r0}}{b^*_{r1}}} \times \sqrt{\frac{1}{\alpha_r \beta_r}} \\ \Rightarrow \quad \frac{\chi_1}{\chi_0} = \left[\frac{z^*_{r1}}{z^*_{c0}}\right]^{\text{MID}} \times \left[\frac{z^*_{r0}}{z^*_{r1}}\right]^{\text{SMALL}} &= \sqrt{\frac{\lambda}{b^*}} \end{aligned} \tag{27}$$

The Equations (26) and (27) are identical to (16) and (18). Hence, identification of b^* and λ follows exactly the identical method described for our baseline model. Therefore, the estimation results in Table 5 apply in this case as well. Given the estimate of $b^* = 0.9434$ and $\lambda = 0.8880$, we get that $\omega = 1.03$. Hence, in terms of the fundamental preference parameter, the state government has a 3% higher weight on economic development than forest conservation. Given that the application cost to the state is significantly lower than that for the center, the state optimally chooses to be more stringent in approving projects, i.e., $b^* < 1$. Therefore, we can not infer about the consequence of decentralization by just examining the value of b^*. We need to evaluate b^* *relative to* λ to understand how state government would differentially trade-off development and conservation.

8.2 Selection vs Sorting under Decentralization

The decentralization policy in our context is implemented at specific thresholds (20 and 40 Ha.). Hence, in addition to the selection problem we modeled, there is also a sorting of projects close to the thresholds (as indicated in Fact 1 and Figure 4 previously). To examine the impact and relative importance of sorting, we augment our baseline static model with the possibility of applicants applying to a different level of government by changing the project size, when the optimal size is close to the threshold. This allows us to decompose the higher empirical density observed to the left of threshold (Figure 4) into selection and sorting.

Consider a project with true quality and size $\{z, S\}$. Based on the "ideal" size, let g be the government that the application would have to be approved by. However, the applicant now faces an incentive to manipulate the size of her application and report a size S', also in the neighborhood of the threshold, so as to be approved by a government g'. The key gain from manipulation is either a higher weight that g' puts on the project and/or lower costs of applying to g'. Note for completeness of the argument, that manipulation will also change the valuation of the project and its application cost, thereby, changing $\phi(S)$ and $\psi(S)$ to $\phi(S')$ and $\psi(S')$. However, for exposition purposes, we assume that they these functions are sufficiently concave near the threshold such that effect of marginal changes in S on approval probabilities and application costs can be ignored. The first order effect of manipulation will come from difference in b_g and λ_g across governments. We therefore analyze sorting by fixing S and letting the applicant choose which government to apply under. Sorting, however, is costly, since it involves planning the implementation of the project with a (marginally) different size. The sorting or manipulation cost is denoted by an increasing and convex function $c_M(S)$.

We define $\tau(S) = c_M(S)/c_A(S)$ and make two assumptions: first, we assume that $\tau'(S) > 0$ i.e., it is costlier to manipulate larger projects as compared to smaller ones. Second, we assume that $\tau(S) > |b - \lambda|$ i.e., the costs are "sufficiently large" such that not everyone would want to manipulate. The second assumption draws from the empirical fact that we observe non-zero density in the number of applications on either side of the threshold. Lastly, from the previous discussion, we would like to remind the reader that:

$$z_c^* = \frac{1}{\sqrt{\phi(S)\psi(S)}} \qquad \text{and} \qquad z_r^* = \sqrt{\frac{\lambda}{b}} \times \frac{1}{\sqrt{\phi(S)\psi(S)}}$$

Lemma 4 *An applicant would never want to manipulate to move from a regional government to the Central government as long as $\tau(S) > b - \lambda$.*

See Appendix B.5 for the proof.

Lemma 5 *All projects with a quality $z \geq z_M^*(S)$ will manipulate their projects from the Central to Regional government, where*

$$z_M^* \equiv M z_c^* = \sqrt{\frac{\lambda + \tau(S) - 1}{b - 1}} \times z_c^*. \tag{28}$$

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

See Appendix B.6 for the proof.

Sorting at 40 Ha.: We now decompose the discontinuous density observed in Fact 1 into selection and sorting. We do this separately for 40 Ha. and 20 Ha. The ratio of the density of projects in post- and pre-period to the left of the 40 Ha. threshold can be given by:

$$
\begin{aligned}
\frac{\xi_{1r}}{\xi_{0c}} &= \frac{(1-F(z^*_M)) + (1-F(z^*_{1r}))}{1-F(z^*_{0c})} \\
&= M(40)^{-\theta}\left(\frac{z^*_{1c}}{z^*_{0c}}\right)^{-\theta} + \left(\frac{z^*_{1r}}{z^*_{0c}}\right)^{-\theta} && \text{(From Equation 9)} \\
&= \underbrace{\left[M(40)\sqrt{\frac{1}{\alpha_c\beta_c}}\right]^{-\theta}}_{\text{Sorting}} + \underbrace{\left[\sqrt{\frac{\lambda}{b}}\sqrt{\frac{1}{\alpha_r\beta_r}}\right]^{-\theta}}_{\text{Selection}} && \text{(From Equation 13)}
\end{aligned}
$$

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 is 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.

9 CONCLUSION

We examine the consequence of decentralized environmental policy-making in India on conservation and economic development. We compile project level data on the universe of proposals requiring diversion of forest land for economic purposes that were submitted to the Indian government for approval during the period 1990-2009. Our identification comes from a rule change in 2004 that increased the upper limit on the size of a project that state governments could approve. The projects with sizes that fall between the previous and post-reform limits, therefore, experienced a switch in their approving authority from the central to the state government. We show that approval probability reduced by 9 percentage points because of decentralization. However, we also find that the density of applications is significantly higher under the state government relative to the center, suggesting that applicants prefer to apply to the state government. We propose a model that endogenizes both applications and approvals to structurally recover the state government's relative preference weight on development work and relative application cost under state. We find that state governments put 9% lower weight on economic value of projects and also have 11% lower application cost. The lower application cost results in 6% increase in the mass of applications, overwhelming the first effect. Our analysis, therefore, unpacks the overall effect of decentralization into direct effect, due to differential preferences and application costs under the two governments, and the indirect effect, through the channel of selection that such preference and cost differences induce. Moreover, we find that the average quality of approved projects also falls due to the selection effect. Hence, decentralization increases deforestation and at the same time, reduces the quality of sanctioned development work. A dynamic version of the model, where the approval process in any period is endogenous to government's past behavior, highlights that the state government fundamentally cares more about economic development, and yet chooses a lower preference weight due to its significantly low application cost. The paper therefore sheds light on the different forces at work when decision-making regarding conservation is decentralized. Importantly, it informs us that when application for legal deforestation is endogenous, consequence of decentralization depends critically on the differential application cost.

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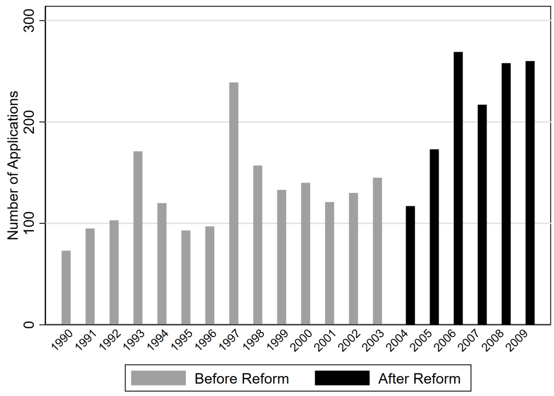
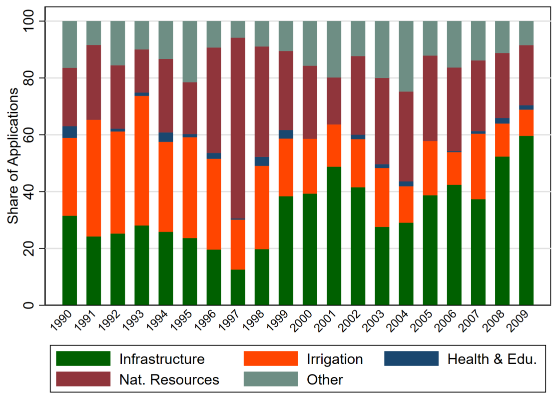
APPENDIX

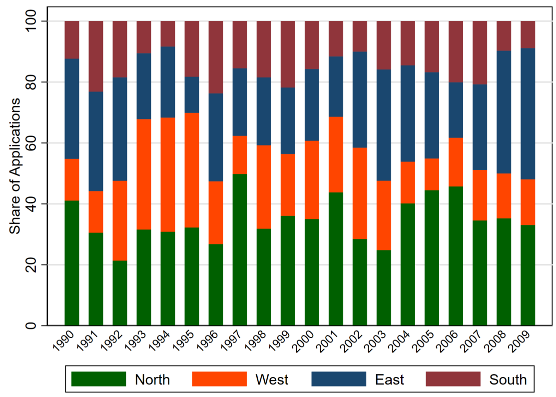
A Tables and Figures

Figure A1—Summary Characteristics of Project Applications



(a) Number of Applications



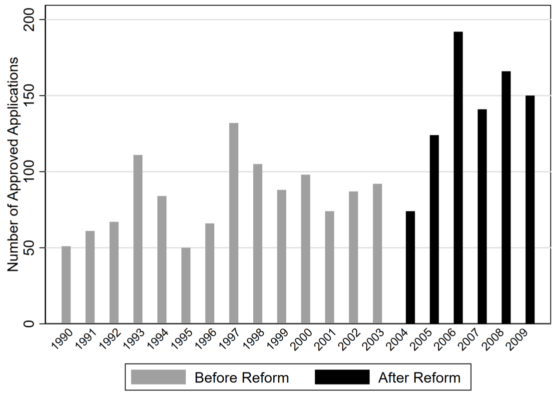


(b) Types of Projects

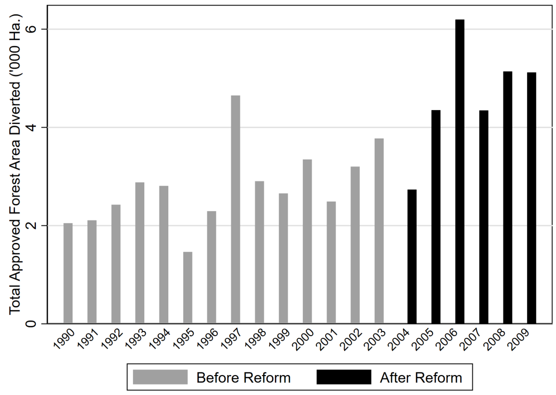
(c) Project Across Regions

<u>*Notes:*</u> The above figure shows the distribution of the number of applications over time. Figure (a) shows the total number of applications in each year. Figures (b) and (c) report the fraction of applications in a year across the type of projects and regions respectively.

Figure A2—Number and Area of Approved Projects



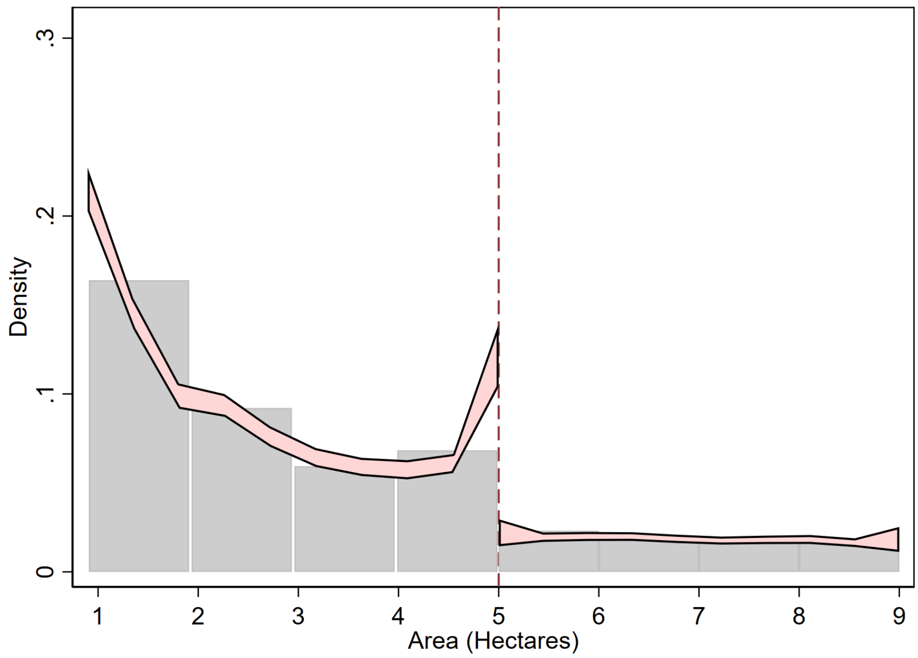
(a) Number of Projects



(b) Total Area

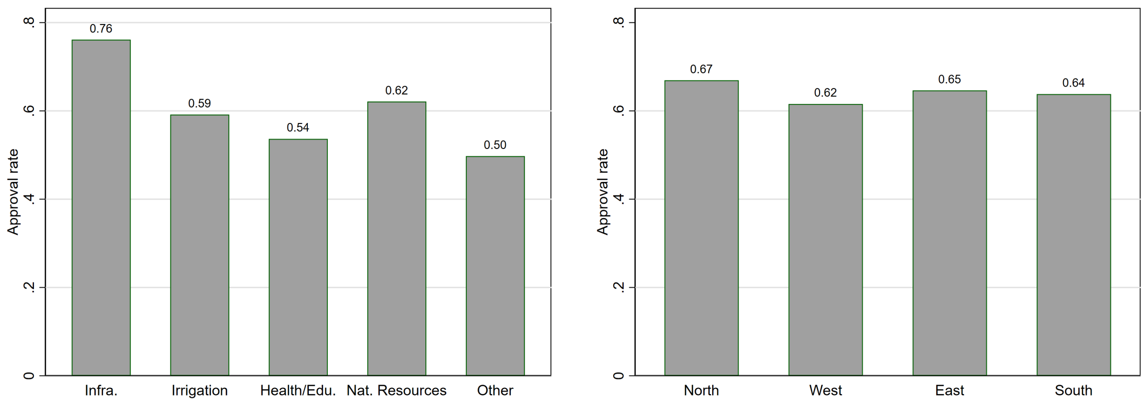
Notes: Figures (a) and (b) report the total number of approved projects and total area of approved projects across years.

Figure A3—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.

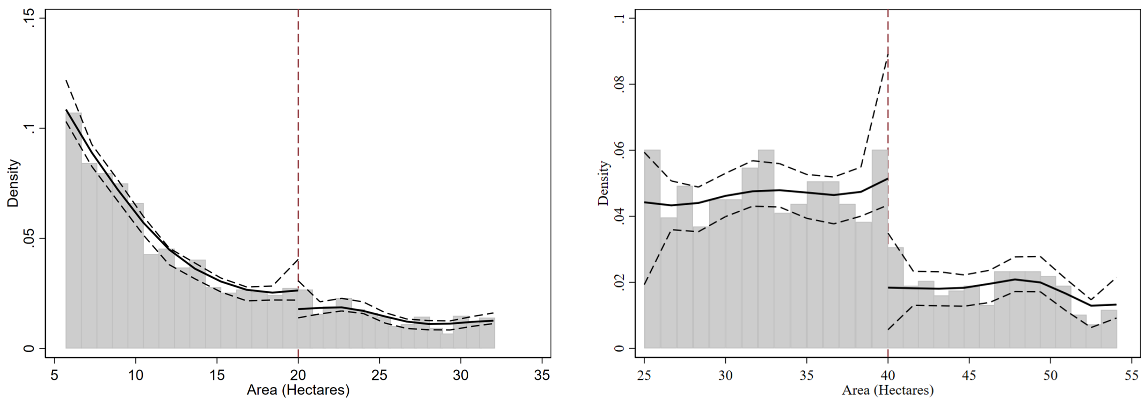
Figure A4—Approval Rates of Projects



(a) Across Project Types **(b)** Across Regions

Notes: Figures (a) and (b) report the average approval probability across project categories and regions respectively.

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—Approval Rates and Forest Cover (Restricted Sample)

	1(Project Approved)					
	Below Median			Above Median		
	(1)	(2)	(3)	(4)	(5)	(6)
Post	0.004			0.004		
	(0.023)			(0.054)		
Middle	-0.044	-0.031	-0.028	0.101*	0.110**	0.089*
	(0.033)	(0.024)	(0.023)	(0.049)	(0.050)	(0.046)
Large	-0.034	-0.026	-0.014	0.156**	0.153**	0.115**
	(0.043)	(0.039)	(0.045)	(0.067)	(0.062)	(0.047)
Middle × Post	0.034	0.027	0.025	-0.121**	-0.128**	-0.115**
	(0.033)	(0.022)	(0.022)	(0.054)	(0.050)	(0.048)
Large × Post	0.042	0.035	0.016	-0.052	-0.034	-0.007
	(0.056)	(0.045)	(0.055)	(0.046)	(0.047)	(0.048)
Mean|Small,Pre	0.82	0.82	0.82	0.76	0.76	0.76
R2	0.05	0.08	0.18	0.08	0.11	0.20
N	802	802	770	868	868	829
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 forest cover in a district in the year 2000 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 A3—Approval Rates and Nightlights (Restricted Sample)

	1(Project Approved)					
	Below Median			Above Median		
	(1)	(2)	(3)	(4)	(5)	(6)
Post	0.023			-0.015		
	(0.019)			(0.032)		
Middle	0.055	0.073	0.049	0.003	-0.005	-0.026
	(0.068)	(0.068)	(0.068)	(0.016)	(0.027)	(0.025)
Large	0.110**	0.117*	0.061	0.035	0.034	-0.004
	(0.049)	(0.053)	(0.051)	(0.042)	(0.046)	(0.035)
Middle × Post	-0.068	-0.082	-0.065	0.046	0.053***	0.099**
	(0.047)	(0.059)	(0.062)	(0.034)	(0.016)	(0.032)
Large × Post	-0.035	-0.036	0.011	-0.006	-0.010	0.008
	(0.059)	(0.065)	(0.065)	(0.019)	(0.022)	(0.023)
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 A4—Probit Specification: Approval Rates and Govt.

	1(Project Approved)			
	(1)	(2)	(3)	(4)
Post	0.144		0.207*	
	(0.102)		(0.119)	
Middle	0.315***	0.310***	0.301***	0.286**
	(0.097)	(0.096)	(0.115)	(0.116)
Large	0.338***	0.339***	0.430***	0.421***
	(0.101)	(0.101)	(0.096)	(0.099)
Middle $\times$ Post	-0.253*	-0.236*	-0.292**	-0.265*
	(0.131)	(0.126)	(0.143)	(0.146)
Large $\times$ Post	-0.036	-0.044	-0.079	-0.076
	(0.142)	(0.136)	(0.132)	(0.133)
N	3105	3105	2153	2153
State FE	Yes	Yes	Yes	Yes
Category 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 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 A5—Time Required Until Stage 1 Project Approval

	Days to Approval					
	(1)	(2)	(3)	(4)	(5)	(6)
Post	-185.200***			-210.488***		
	(49.270)			(59.504)		
Middle	-83.384	-91.733*	-127.069***	-84.663	-97.899	-123.463*
	(53.227)	(47.737)	(43.149)	(71.591)	(69.494)	(70.551)
Large	6.255	1.472	-28.028	0.428	-2.302	-34.305
	(55.529)	(52.133)	(40.669)	(63.754)	(63.808)	(60.058)
Middle × Post	91.512*	93.851*	126.119**	86.835*	93.846*	117.723**
	(53.332)	(50.441)	(46.399)	(46.865)	(47.087)	(47.414)
Large × Post	24.408	19.570	46.428	17.625	10.513	45.365
	(68.139)	(68.197)	(63.950)	(66.409)	(68.826)	(75.261)
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
Category FE	Yes	Yes	No	Yes	Yes	No
State FE	Yes	Yes	No	Yes	Yes	No
Year FE	No	Yes	No	No	Yes	No
State-Year, Cat. 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 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 A6—Time Required Until Stage 2 Project Approval

	Days to Approval					
	(1)	(2)	(3)	(4)	(5)	(6)
Post	-251.308***			-271.525***		
	(44.510)			(68.931)		
Middle	-279.050***	-284.549***	-278.573***	-283.170***	-289.949***	-274.469***
	(57.048)	(55.393)	(63.223)	(57.162)	(59.708)	(61.869)
Large	-22.034	-18.456	-14.322	-27.344	-17.441	-7.331
	(61.523)	(62.894)	(46.303)	(67.112)	(72.249)	(69.380)
Middle × Post	180.302***	183.697***	189.398***	138.050*	132.709*	131.641
	(54.249)	(46.273)	(63.237)	(69.018)	(68.169)	(89.410)
Large × Post	117.379	129.613	131.106	88.985	82.939	87.445
	(82.042)	(90.089)	(94.009)	(106.838)	(112.722)	(139.298)
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
Category FE	Yes	Yes	No	Yes	Yes	No
State FE	Yes	Yes	No	Yes	Yes	No
Year FE	No	Yes	No	No	Yes	No
State-Year, Cat. 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 A7—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 A8—Threshold Project Quality and Approving Government

	Log Employment Generated			
	(1)	(2)	(3)	(4)
	Minimum	1 Pct.	2 Pct.	3 Pct.
RD Estimate	1.728	1.724	1.640	1.260
	(0.886)	(0.893)	(0.843)	(0.768)
Con. p-value	0.051	0.053	0.052	0.101
Robust p-value	0.093	0.102	0.084	0.124
Bandwidth	11.48	11.34	12.46	16.95
N	96	96	96	96
BW Type	CCT	CCT	CCT	CCT

Notes: The above table reports the RD estimate 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.

Table A9—Average Project Quality and Approving Government

	Log Employment Generated					
	(1)	(2)	(3)	(4)	(5)	(6)
Middle	0.423***	0.388***	0.367***	0.506***	0.496***	0.426***
	(0.133)	(0.127)	(0.089)	(0.131)	(0.134)	(0.112)
Large	1.046***	0.991***	0.972***	1.137***	1.111***	1.091***
	(0.197)	(0.196)	(0.174)	(0.242)	(0.245)	(0.214)
p-val: $\beta_M = \beta_L$	0.00	0.00	0.00	0.02	0.03	0.01
R2	0.19	0.21	0.29	0.22	0.23	0.33
N	2067	2067	2006	1282	1282	1226
State FE	Yes	Yes	No	Yes	Yes	No
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	Whole	Whole	Whole	Restricted	Restricted	Restricted

Notes: The sample is the universe of applications between 10-100 Ha. received in the time period 2014-2021. The dependent variable is the proposed (log) employment generated as reported on the application. 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 15-25 hectares and 35-45 hectares. Columns (1) and (4) include state and project category fixed effects, while Columns (2) and (5) add year fixed effects. Columns (3) and (6) instead include state-project category fixed effects along with year fixed effects. p-val: $\beta_M = \beta_L$ reports the p-value to test whether the coefficients on Middle (β_M) and Large (β_L) are equal to each other. Standard errors are clustered at the state and project-category level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

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 (7)-(9) from their corresponding theoretical counterparts. Turning to Equations (10), 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:

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

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

$$\begin{aligned}
V(P_g) &= \int_{z\geq z_g^*(S)} \Big[P_g(z,S)-\overline{P}_g(S)\Big]^2\frac{dF_z(z)}{1-F_z(z_g^*(S))} \\
&= \int_{z\geq z_g^*(S)} P_g^2\frac{dF_z(z)}{1-F_z(z_g^*)} + \overline{P}_g^2 - 2\overline{P}_g\underbrace{\int_{z\geq z_g^*} P_g\frac{dF_z(z)}{1-F_z(z_g^*)}}_{=\overline{P}_g} \\
&= \int_{z\geq z_g^*(S)} P_g^2\frac{dF_z(z)}{1-F_z(z_g^*)} - \overline{P}_g^2 && \text{(See Equation 10)} \\
&= \frac{\theta}{\theta-2}\overline{P}_g^2 - \overline{P}_g^2 \\
&= \frac{2}{\theta-2}\overline{P}_g^2
\end{aligned}$$

B.4 Proof of Proposition 3

The Bellman equation can be written as

$$\Pi_g(R) = \max_{b_g}\omega_g V + c_0(R-D) + \delta\Pi_g(R-D)$$

FOC w.r.t. b_g gives us

$$\frac{\theta}{2}\omega_g b_g^{\frac{\theta}{2}-1}\lambda_g^{1-\frac{\theta}{2}}\Gamma_V(R) - (c_0+\delta\Pi_g^{'}(F-D))\left(\frac{\theta}{2}+\frac{1}{2}\right)b_g^{\frac{\theta-1}{2}}\lambda_g^{\frac{1-\theta}{2}}\Gamma_D(R) = 0 \tag{29}$$

Let $V^*(R)$ and $D^*(R)$ be the optimized values of V and D. Then,

$$\Pi_g(R) = \omega_g V^*(R) + c_0(R-D^*(R)) + \delta\Pi_g(R-D^*(R))$$

Differentiating w.r.t. R we get,

$$\Pi_g^{'}(R) = c_0 + \delta\Pi_g^{'}(R-D^*(R))$$

$$\Rightarrow \quad \Pi_g^{'}(R) - \delta\Pi_g^{'}(R-D^*(R)) = c_0$$

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

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

Using this in equation (29) gives us

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

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

$$\Rightarrow \quad b_g^* \;=\; \omega_g^2\lambda_g\kappa(R) \quad \text{where } \kappa(R) = \left[\tfrac{\theta}{\theta+1}\tfrac{1-\delta}{c_0}\tfrac{\Gamma_V(R)}{\Gamma_D(R)}\right]^2$$

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:

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

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

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:

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

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.