Land for Opportunity?
Deprivation and Immobility in Rural India*

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Abstract

We examine how land ownership shapes educational mobility in rural India. Using full-count rural census microdata, we document a robust step-function pattern across the land distribution: educational mobility rises sharply from the landless to marginal landholders and then plateaus. Exploiting historical variation in British-era land-tenure regimes, we demonstrate a causal link between higher landlessness and lower educational mobility. To unpack mechanisms, we develop a model where parents allocate children's time between school and work under a subsistence constraint. With little or no land, the constraint binds, increasing child labour and suppressing schooling; a small rise in land relaxes it, producing a sharp drop in child labour and a jump in schooling and upward mobility. The framework endogenously generates the step-function, matches the core facts, rationalizes heterogeneities, and yields testable predictions that we validate.

JEL: Q15; J62; I24; O15

Keywords: land inequality; intergenerational mobility; education; development

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All errors are my own.

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Introduction

Equality of opportunity is a normative ideal that requires equal access to basic liberties, capabilities, and prospects in life for all individuals regardless of circumstance and is at the heart of notions of fairness, equity, and justice (Rawls, 1971; Sen, 1980). A common thread in the vast literature focused on equality of opportunity is an emphasis on access to basic education for all (Roemer and Trannoy, 2016). To quote Sen (1999), "education is crucial beyond its role in production; its most important role [is] increasing human capability and therefore choice."

The emphasis on education as a lever to level the playing field is especially salient in rural India. For decades after independence, rural India was characterized by chronic under-provision of elementary education[1]. The late 1980s and 1990s saw a marked shift in policy objectives towards the aim of providing universal access to free elementary schooling for all [2]. Over this period literacy rates in rural India almost doubled from 36% in 1981 to 68% in 2011, signaling a substantial expansion of educational opportunities. However, the degree to which such opportunities were shared across socio-economic strata is unclear. Rural India is home to endemic poverty and deep rooted inequities in wealth, income, and social status. Despite the universalization of free elementary schooling, it is conceivable that this expansion of opportunity has only meaningfully benefited those whose socioeconomic status makes them sufficiently invulnerable to the constraints and risks of life in rural India.

We seek to shed light on this issue and ask how important the socioeconomic status of parents is in giving children access to basic educational opportunity. To answer this question, we examine how land ownership affects the likelihood that children whose parents do not have any schooling attainment, attain minimal levels of schooling, that is, the likelihood that they experience upward educational mobility (mobility). Our focus on land as a measure of socioeconomic status is motivated by the fact that rural India is primarily agrarian and, as such, land is the most important income generating asset, accounting for nearly three-quarters of total wealth owned by rural households [3]. Employing novel full-count census data from the Socio-Economic and Caste Census of 2011, we document a striking non-monotonicity, a step function pattern in the land-mobility relationship. As land ownership increases from zero to the first acre, mobility likelihood increases sharply, following the first acre additional land wealth delivers little to no mobility gains. This pattern arises across most states in our sample, and exists despite the fact that the upper bound on mobility likelihood is well below 100% across those states. Landlessness is the key constraint on mobility. Conditional on parents having no formal education, their owning about 1 acre of land increases the probability of their children's educational upward mobility by between 8% and 35% vis-a-vis children born into landless households. This range varies by state with, in general, poorer states exhibiting larger landed-landless mobility gaps.

To causally identify the mobility-landlessness relationship, we exploit a historical experiment created by British land tenure policy in the state of Maharashtra. British policy forged a discontinuity

[1]Throughout the 1950's, 60's and early 70's public outlays on education were on average a modest 1.5% of GDP, and basic schooling was characterized by thin staffing of teachers, multi-grade classrooms, and severely inadequate facilities; (Government of India, 1966).

[2]Public education expenditure rose to about 4.28% of GDP by 2000–01 (Center + States), before moderating to between 3.5–3.8% in the late 2000's (Ministry of Education, 2009).

[3]MOSPI, *Press Information Bureau, 2014*

in land tenure regimes across the border of the Konkan administrative division, which manifests today in a discontinuously higher landlessness inside the Konkan than just outside the region. We exploit this experiment in a spatial fuzzy regression discontinuity design, to show a causal relationship between landlessness and educational mobility. Our causal estimates suggest that being landless reduces mobility likelihood by between 10 and 16 percentage points, an effect close in magnitude, to the 8.4 percentage point gap between the landless and marginal landowners for Maharashtra as a whole.

We rationalize these observations with an economic model whose features are informed by the Indian rural setting. Schooling is free but uneven in quality and access, child labour is common and more productive with age, there is regional and seasonal variation in wages, and most importantly households face subsistence needs. Human-capital accumulation spans two stages (primary then middle school), with effort in the first stage more valuable when it is complemented by effort in the second; school quality and availability scale the payoff to each stage. In this setting, even a small plot can relax subsistence pressure, allowing households to substitute time from child labour into schooling. And such a setting delivers a clear threshold effect for land holdings. When holdings are low so that subsistence binds, households rely on child labour to meet subsistence constraints, and incremental land income is spent one-for-one on pulling children out of work and into school, thus producing the sharp rise in educational mobility up to threshold land levels. Beyond that, parents are unconstrained and optimally trade off current child earnings against future returns to schooling, so the mobility–land gradient flattens. Complementarity across educational stages amplifies this plateau: if later life education effort is bottlenecked - because middle schools are scarce/low quality, and/or adolescent labour demand is strong - then the return to raising early education falls, further muting the post-threshold slope.

The mechanisms of the model map directly to a set of specifications that we run in Section 5.3 of the paper that tests whether correlations predicted by the model are present in the data. Specifically, the model predicts; (i) steep improvements from landlessness to threshold landholding in schooling time and mobility should be coincident with declining child-labour incidence, but that there should be no (or a much more muted) increase in consumption and (ii) stronger post-threshold mobility-land gradients where middle-school access is better and where adolescent labour demand is lower. These predictions find ample support in the data. Going from landlessness to marginal landownership reduces child labor incidence by nearly 50% with minimal decreases with land thereafter. On the other hand, per-capita consumption shows minimal increases up to the first acre of land and sizeable increases thereafter, exactly as our model predicts. Regions with lower middle school availability show smaller mobility-land gradients, as do areas with higher adolescent labour demand.

Our framework also helps explain the heterogeneities in the mobility-land relationship between states. Specifically, the model makes a range of sharp predictions about; (i) the precise determinants of threshold land wealth (ii) the effect of agricultural wages and wage augmenting programs, and (iii) the effect of school quality. We validate these predictions in Section 5.4 and show how they help rationalize the differences in absolute mobility levels, the precise position of the jump in mobility from land and the shape of the land-mobility curve.

This paper contributes to the literature linking land ownership, land inequality, redistribution, and titling to educational outcomes. A quasi-experimental study on Colombia's 1968 land reform by Galán (2024) shows that allocating land to poor rural households raised intergenerational mobility both in income and education. Work on urban land-titling programs in Latin America shows land titling increased investment and improved children's schooling (Galiani and Schargrodsky, 2010). On the other hand Bleakley and Ferrie (2016) show that winners of Georgia's 1820 land lottery realized wealth gains but experienced limited long-run human-capital effects for descendants. Another strand of literature focuses on land tenure history and the effect of land inequality on institutions. Galor et al. (2009) show that land inequality stifled the expansion of education investment in the United States, while Banerjee and Iyer (2005) show that historical land tenure regimes that were extractive in nature cause lower public goods provision including investment in education today. Our documenting of the almost complete importance of the extensive margin is unique in this literature. Our work also introduces a novel mechanism behind the land-education relationship, namely the subsistence alleviating effects of land wealth and the reduced dependence on child labour that frees up children's time for education.

There is a large literature on intergenerational mobility (Chetty et al., 2014b,a; Black and Devereux, 2011), and of particular relevance to this study is the work on intergenerational educational mobility in the developing world (Alesina et al., 2021; Asher et al., 2024; Neidhöfer et al., 2018). We contribute to this work by establishing how mobility is shaped by land ownership and land inequality and identifying this relationship causally. In doing so we also contribute to a related literature that studies how inequality correlates with mobility across countries (Andrews and Leigh, 2009; Björklund and Jäntti, 2009; Corak, 2013) and within countries (Chetty et al., 2014a; Acciari et al., 2022; Fan et al., 2021), see Durlauf et al. (2022) for a review. The consensus of this literature is that more unequal societies exhibit lower intergenerational mobility, its most common expression being the "Great Gatsby" curve. Most work in this literature examines this relationship using aggregate measures of inequality without identifying the key margins of the distribution of wealth or earnings that drive the relationship between inequality and intergenerational mobility. In contrast, we are able to precisely identify the extensive margin of the land distribution as the key margin that matters in this rural context.

Our findings also connect to poverty trap theories in which nonconvexities and missing markets create thresholds below which households remain mired in poverty. This work in development economics started with a focus on nutrition- and work-capacity mechanisms to micro-found such traps (Dasgupta and Ray, 1986). More recent work emphasized wealth- and asset-based approaches to poverty traps and formalized critical asset levels that separate low- and high-accumulation regimes (Carter and Barrett, 2006). Related empirical work has shown that interventions able to push households over asset thresholds can generate persistent gains (Banerjee et al., 2015). We contribute micro-evidence consistent with a threshold at the extensive margin of the distribution of land holdings in accord with the asset-based approaches to poverty traps.

Finally, our work relates to the literature that studies how agrarian conditions shape schooling and child labour through prices, technology, and shocks. Agricultural technological change and returns influence household labour allocations (Rosenzweig and Evenson, 1977); seasonal wages and liquidity needs distort children's time use and schooling (Jacoby and Skoufias, 1997); and income shocks tied to weather or commodity price cycles shift child labour and enrollment (Duryea and Arends-Kuenning, 2003; Kruger, 2007; Maccini and Yang, 2009; Shah and Steinberg, 2017). We add a distinct mechanism which is surprisingly absent from this literature within the agrarian context: *landlessness* as a subsistence constraint that forces households to depend on child labour and, consequently, constrain educational mobility.

Our paper proceeds as follows. In section 1 we introduce our data, we then discuss some key facts on education attainment, land wealth and child labour incidence in rural India. In section 3 we develop and discuss the key stylized facts of our paper. Section 4 addresses causality and section 5 dives into mechanisms, theory, and tests our proposed explanations. Section 6 concludes.

1 Data

The primary data source for this study is India's Socio-Economic and Caste Census (SECC) conducted in 2011. The SECC was a one-time, data-collection exercise, distinct from the regular decennial Population Census. Whereas the Population Census focuses on demographics and housing/infrastructure, the SECC emphasized detailed enumeration of caste and sub-caste categories and the socioeconomic standing of groups in terms of income, asset ownership, and occupation profiles. It was designed to facilitate better targeting of beneficiaries for poverty-alleviation programs. Owing to a lack of standardization in caste and sub-caste categories across states, the core caste-enumeration data were withheld; publicly available SECC data report caste only in broad Scheduled Caste (SC), Scheduled Tribe (ST), and general (forward caste) categories, and aggregates are released at the tehsil and district levels.

We have access to full-count rural SECC micro-data for ten Indian states covering approximately 585 million individuals—about 70.1% of the country's rural population in 2011 [4]. For each co-resident household member, the data include demographics, educational attainment, occupation, and relationship to the household head. On caste, we only observe the standard SC, ST and general categories. At the household level, data record land owned (acres), irrigation status, income bands, sources of income, ownership of agricultural assets and implements, and dwelling characteristics [5]. The dataset also identifies the place of residence of each household down to the village name. Thus, it provides us with linked parent child educational outcomes (conditional on co-habitation at the time of enumeration) which allows us to trace mobility over the entire land distribution. Village identifiers align cleanly with other administrative datasets[6], enabling high-quality merges with various survey and administrative datasets. Its scale allows us to condition on parental education *within* land bins, including the sparsely populated right tail of the land distribution.

Most importantly, the SECC is the only dataset that can enable our causal inference approach and key aspects of our analysis when testing our theory. The scale and granularity of the data allows us to stay powered when implementing the high-resolution spatial fuzzy RD at the Konkan border. With

[4] States: Punjab, Uttar Pradesh, Bihar, West Bengal, Rajasthan, Madhya Pradesh, Maharashtra, Tamil Nadu, Karnataka and Kerala.

[5] Income bands (thousand Indian rupees per month) for the highest-earning household member: (i) 0–5; (ii) 5–10; (iii) 10 or more.

[6] Ambiguity arises when multiple villages within a tehsil share the same name. In such cases, we use village population as an auxiliary identifier. This procedure works well when merging SECC to the Population Census Primary Census Abstract (PCA). For example, in Uttar Pradesh we uniquely match all but 1033 of nearly 109,000 villages.

the SECC, we are able to establish the sharp discontinuity in landlessness produced by the historical experiment and the resulting discontinuities that emerge in mobility outcomes as a result of it. The scale and multistate coverage also help us exploit granular variation in schooling environments and land productivity that we use to probe mechanisms and to validate our theoretical framework.

In addition to the SECC, we use several complementary census and survey sources. From the 2011 Population Census, we use the PCA and the Household Amenities tables to obtain village-level demographics, infrastructure and shape-files. These data are extracted from the SHRUG open-data portal and are used at various points throughout the study.

We draw on the National Sample Survey (NSS) rounds 61 (2004–05), 66 (2009–10), and 68 (2011–12) for measures of child labour incidence, household land ownership, debt incidence, consumption per capita, and core demographic variables. We will draw on this data extensively when validating mechanisms and when dealing with alternative explanations to our theory in Section 5.

Further, we use the Rural Economic and Demographic Survey (REDS) 2006, which samples 119,000 rural households across 242 villages in 17 states and administers detailed household questionnaires to a subsample of 8765 households. REDS reports education, demographics, primary occupation, migration status, and time use measured over three representative days for all members. REDS also records number of days children spend in school every year as well as land ownership, land-market transaction histories, consumption, income, and related modules. These data will also be important when examining our mechanisms and in providing facts. that contextualize our findings.

We also use the Annual Status of Education Report (ASER) for detailed district level measures of school quality including infrastructure, teacher absenteeism, etc.

Finally, we use data from the Food and Agriculture Organizations (FAO) GAEZ data portal on measures of predicted productivity for 44 major crops sown in India, to capture variation in the agricultural productivity of land.

2 Context: Land and Education in Rural India

This section provides some context on educational attainment, incidence of child labor, and distribution of land holdings in rural India. Our focus on these variables is motivated by the core findings and mechanisms of our study. Educational mobility is the object of interest; thus, diving deeper into the levels of educational attainment among the cohort of parents and adults in rural India is important to underscore the importance of mobility and motivate our choice of measures. Given our finding of the central role of even minimal land ownership in increasing mobility, we dive deeper into the distribution of land holdings and document some key facts about how unequal the land distribution is and what proportion of the population is deprived of land ownership. Finally, given the importance of child labor in our analysis as the mechanism through which land deprivation and subsistence constraints reduce mobility, we document its prevalence and refer to existing evidence on its consequences.

According to the 2011 population census, the adult literacy rate in rural India stood at 68% , comparable to South Asian neighbors Bangladesh & Nepal but well below Southeast Asian benchmarks like Indonesia and Vietnam (94.8% and 94.5% rural adult literacy respectively)[7]. However, the

[7]The the adult literacy rate defined for all individuals aged 15 or above for all aforementioned countries. The decennial

technical definition of literacy subsumes within it educational levels ranging from college education to below primary school attainment. Thus, the headline figure of 68% masks how little education the representative rural Indian has. Therefore, we look closer at educational attainment levels across the population (for the ten states for which we have data) using the SECC, which reports for each individual their highest level of education completed classified into the following categories; (i) Illiterate, (ii) Literate less than primary school, (iii) Primary School, (iv) Middle School (grade eight), (v) Secondary (10th grade), (vi) Senior Secondary (12th grade), (vii) College or above. In Table 1 we report the the modal and median level of education for the population of adults (aged 18 +) for all males, females and household heads[8]. The findings are stark: the modal adult is illiterate, and the median adult has at most primary school attainment; among household heads the median is literate but below primary, and women lag men with a median below primary as well. Finally, a little less than half of the population of adults has below primary school education status, with just over half of all household heads falling into that category as well. Most working-age adults never reach middle school (a little under two-thirds) , and most household heads (the parents in our data) never clear primary school. One should also keep in mind that the literature on education and human capital in India finds that even clearing primary or middle school officially may not map well into basic skills like reading comprehension and mathematical ability (ASER Centre, 2019, 2024; World Bank, 2018; Kaffenberger and Pritchett, 2021; Banerjee et al., 2007). These findings further emphasize the importance of educational mobility given the thin stock of human capital in rural India.

Table 1: Modal and median education by group

Group	**N**	**Modal**	**Median**	**Below Primary**	**Below Middle**
HH Heads (18+)	105,828,630	Illiterate	Literate < Primary	52.3%	69.1%
All adults (18+)	371,956,606	Illiterate	Primary	48.6%	63.4%
Males	192,822,041	Illiterate	Primary	—	—
Females	179,134,565	Illiterate	Literate < Primary	—	—

Notes: "Modal" is the most frequent education category; "Median" is the median category. "Literate < Primary" = literate but below completed primary. Below Primary is the share of individuals who haven't completed primary school i.e fifth grade, below middle school is the share of individuals that never complete eighth grade.

We turn next to child labour. Child labour for those aged 14 and under has been formally restricted since the 1986 Child Labour (Prohibition and Regulation) Act, but coverage remained partial and enforcement weak. Agriculture and family enterprises, the dominant employers of child labour, were largely outside the core prohibitions, so the policy mainly targeted listed hazardous industries. Evidence also suggest that bans can generate negative income effects that *raise* child work when households lose earnings; consistent with this, Bharadwaj et al. (2020) document increases in child labour following India's ban. In line with findings in many low-income settings, child and adolescent work remains common. In NSS data 14% of children aged 5–17 report working as their primary activity, rising

census for India scheduled to take place in 2021 was suspended due to COVID and is yet to take place. More recent findings from the NSS 78th round place India's rural literacy rate at 80 5% in 2022.

[8]Household heads are typically the oldest working male residing in the household.

to 30% among those aged 15–17, while UNICEF estimates roughly 28 million children aged 5–14 engaged in work circa 2011 (UNICEF, 2011). Given the high incidence of child labour in our setting, its importance to family income and how sharply its incidence rises as children grow up, its importance in explaining how and why children fall behind in school and fail to acquire sufficient human capital, cannot be overstated. A large literature finds that child labour crowds out schooling time and depresses learning and later human capital—see, for example, Beegle et al. (2009); Heady (2003); Gunnarsson et al. (2006); Rosati and Rossi (2003); Basu and Tzannatos (2003). We will explore in more detail how child labour features in the land-educational mobility relationship in the mechanisms section of the paper.

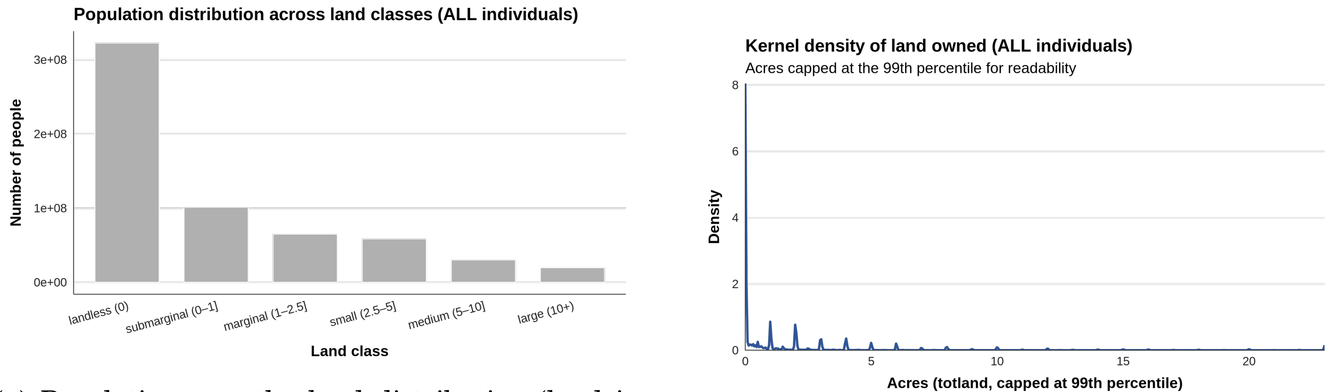
We now use the SECC to look closely at the distribution of land holdings. Our measure of land ownership is defined at the household level, i.e total land owned by the household, thus for each individual in our data the land owned figure is that held by the household as a whole. Figure 1a shows a histogram of how population mass is distributed across landholding categories[9] ; Figure 1b smooths the same distribution and shows a density plot of the population over landholdings. The figures paint a clear picture; most of rural India is either landless or has a small parcel of landholding smaller than an acre. Our data show that 54% of the population is in landless households, 71% in households that own less than one acre of land, and only about 8.3% in households with more than 5 acres of land. In other words, in rural India, landlessness is the norm and land inequality is very high. Bauluz et al. (2020) show that among a set of developing countries, India has one of the highest levels of landlessness (39% of households)[10], level with Bangladesh and Ethiopia and behind only Guatemala (56% of households). This level of deprivation is striking given the degree of dependency of agrarian India on land as a source of income and work[11]. Appendix table 10 using NSS data on per-capita consumption and landholdings, clearly shows a strong gradient in landholdings and living standards, at least as measured by consumption.

Together, the low levels of schooling in rural India, the importance of land for agrarian livelihoods, and its highly unequal distribution, further underscore the need to thoroughly examine how educational mobility is shaped by land ownership. Is it the lack of land ownership and the vulnerability that comes with it, that limits schooling and human capital accumulation? We turn next to this question. We examine how the likelihood of educational mobility changes with land ownership and develop the key stylized facts of the paper.

[9]These categories are minor iterations on official categories used by the Ministry of Agriculture & Farmers Welfare, see Agriculture Census 2015–16, Chapter 1. We make the following changes; (i) We work with acres rather than hectares (ha) as our unit of measurement of land, 1 acre $\approx$ 0.4 hectares. (ii) We break up the officially used marginal category i.e. less than 1 ha into three distinct categories; landless; 0 acres, sub-marginal; between 0 and 1 acres of land and marginal; between 1 and 2.5 acres of land. We make these changes in order to show a more granular distribution of the population over landholdings since an overwhelming mass of individuals lies below 1 ha.

[10]Their estimates differ from ours likely because they rely on representative administrative surveys for India as a whole rather than the full count census for the 10 states we look at.

[11]70% of India's rural population depends on agriculture as the main source of livelihood according to The 2019-20 Economic Census of India.



(a) Population over the land distribution (land in Acres)

(b) Population density over land (land in Acres)

Figure 1: Population size and density across land distribution.

3 Estimation and Stylized Facts

Numerous approaches have been used to measure intergenerational mobility, reflecting the diversity in views about what the measure means, the differences in normative considerations that undergird scholarly work, and the constraints in data availability. A useful way to organize intergenerational mobility measures is along two orthogonal dimensions.

(i) Directionality: *Directional* measures focus on upward movement only (e.g., the share of children who surpass their parents), whereas *non-directional* or *exchange* measures treat upward and downward moves symmetrically and quantify overall re-ranking or movement.

(ii) Absolute vs Relative: *Absolute* measures compare levels (e.g., years of schooling, income), while *Relative* measures compare positions in the distribution (child's percentile versus parents percentile). Most measures used in the literature can be viewed as combining one choice from each dimension, yielding four broad classes (Genicot and Ray, 2023). Appendix table 9 lists examples.

The two dimensions come with clear trade-offs. *Directional* measures have obvious welfare content: they separate genuine upward progress from mere re-ranking. Yet they can mask *who* gains and who loses. A common mitigation is to condition the statistic on parental status—either in levels or by rank—so that upward progress is evaluated within parental strata (Chetty et al., 2014b; Alesina et al., 2021). However, such conditioning localizes the comparison and makes the overall strength of intergenerational persistence across the full distribution blurry; results can also be sensitive to the choice of bins or percentiles. By contrast, *non-directional* (exchange) measures are expressly built to summarize persistence (e.g., rank–rank slopes, elasticities), but they are welfare-neutral with respect to the sign of movement. When the outcome is intrinsically ordered—such as income or schooling, where upward changes are normatively preferred—this neutrality may be unsatisfying.

Absolute versus *relative* measures trade off material meaning against comparability. Absolute measures work in levels (years of schooling, test scores, incomes). Their appeal is interpretive and welfare-laden: they answer whether children are better off in real terms than their parents, which aligns closely with policy goals focused on living standards. The downside is that absolute mobility is easily conflated with macro conditions; growth slowdowns, booms and development (a rising tide lifts all boats). As a result, absolute statistics can move even when the intergenerational *link* is unchanged (Chetty et al., 2014b). Relative measures, by contrast, compare positions in the distribution (ranks/percentiles). They remove aggregate growth and focus on the parent-child association (the copula or transition matrix), producing quantities that are comparable over time and across geographies and speak directly to persistence. But this very invariance makes them normatively austere: if everyone's level rises equally, relative mobility may not budge, masking large material gains; and because they are ordinal, they compress information on *how much* outcomes change (a one-quantile move counts the same everywhere). Relative measures also require detailed panel data that measures representative/final outcomes for both parents and children at similar points in their life cycle, placing significant constraints on inquiry especially in the developing world where such data is scarce.

Given that our object of interest is the likelihood that a child born to low-education parents attains education given that more schooling is unambiguously preferable to less schooling due to its substantial effects on earnings growth, structural transformation, and occupational mobility (Banerjee and Newman (1993); Foster and Rosenzweig (1996); Duflo (2001); Munshi and Rosenzweig (2006); Hsieh et al. (2019); Porzio et al. (2022); Khanna (2023)), we adopt a *directional* measure of mobility that registers gains when a child attains more education than the parent. Furthermore, our objective is to trace how mobility varies over the *cross-sectional* distribution of landholdings at a given point in time, not to compare cohorts or normalize away aggregate growth. In addition, the census links only co-resident parents and children, so a child's terminal attainment is often unobserved. For these reasons, we work with an *absolute*, level-based measure (the highest grade of schooling attained by a child) rather than a rank-based measure, and report measures conditional on parental schooling strata. Specifically we define;

$$IM^1 = \mathbf{1}\{\mathrm{E}_c \geq 1 \mid \mathrm{E}_p = 0, X_c \in [12, 18]\} \tag{1}$$

$$IM^2 = \mathbf{1}\{\mathrm{E}_c \geq 2 \mid \mathrm{E}_p = 0, X_c \in [15, 18]\} \tag{2}$$

Where E_c and E_p are the highest grade of schooling attained by the child and the father, respectively, and X_c is the age of the child. $E_c \geq 1$, is true if the child has completed primary/elementary (5th grade) school or more and $E_c \geq 2$ is the analog for middle school attainment (eighth grade). $E_p = 0$ is true if the father is either literate with below primary school attainment or illiterate, the median level of education for household heads and fathers in our setting. As appendix figure 9 shows, this level of attainment corresponds to the majority of fathers across states[12]. Thus, in most states, we evaluate mobility from the median parental attainment level. The age restriction for children is motivated by two reasons; first, children typically finish primary school at ten or eleven years old and middle school at fourteen or fifteen years old, making the lower bounds on the age selection necessary to prevent mechanically downward biasing the estimates. Second, for any census dataset where the joint outcome distribution of parents and children is observed conditional on cohabitation, the upper bound on the age bracket is necessary to avoid cohabitation selection bias, another source of downward bias in the mobility measure. (Card et al., 2022). The choice of the precise upper bound at eighteen years is motivated by the fact that cohabitation rates in India remain high till age eighteen falling sharply

[12]With the exception of Kerala, Maharashtra and Tamil Nadu.

post eighteen for both boys and girls[13].

To understand how mobility likelihood changes over the land distribution we run the following linear probability model at the father-child pair level;

$$IM^k_{iv} = \alpha_0 + \sum \beta_L \mathbf{1}\{i \in L\} + [\theta_v + \gamma_{c(i)} + \delta_{o(i)} + \eta_{f(i)}] + \epsilon_i \tag{3}$$

Where i indexes the father-child pair, let L denote the household's land classes we used earlier: *landless* (omitted), *submarginal* (0-1 acres) *marginal* (1–2.5 acres), *small* (2.5–5 acres), *medium* (5–10 acres), and *large* (10+ acres). The coefficients β_L measure the change in probability of upward mobility from land ownership *relative to the landless*, conditional on village fixed effects (θ_v), caste fixed effects (γ_c), child birth–cohort effects (δ_o), and father birth–cohort effects (η_f). Alongside regression estimates, we also report raw mobility averages across land classes. Given India's substantial developmental, cultural, demographic, and agro-climatic heterogeneity, we estimate and display results separately by state in Figure 2. Coloumns (a) and (c) of figure 2 shows results from equation 3 over the land distribution for IM^1 and IM^2 respectively, while panels (b) and (d) show the raw mobility probabilities over the land distribution. The results in figure 2 point to a striking pattern: in seven of the ten states in our sample— Uttar Pradesh (UP), Bihar, Maharashtra, Punjab, West Bengal, Karnataka and Tamil Nadu, states which account for 55.6% of India's rural population— (i) the likelihood of upward mobility increases steeply from zero land to roughly the first acre and then quickly plateaus, with minimal gains from additional land thereafter, and (ii) even among large landowning households, the rate of upward mobility is well below 100%[14]. These patterns are consistent for both measures in 1 and 2.

The first order takeaway from these results is clear; the extensive-margin of land ownership plays the dominant role in the land–mobility relationship; land deprivation is the core driver of immobility and intensive-margin variation in land size contributes comparatively little after the first acre or so. Although the importance of land ownership for educational mobility is not surprising given the significant impact of land wealth on living standards and the findings of earlier work in India that emphasizes the strong association between land inequality and underdevelopment (Besley and Burgess, 2000; Banerjee et al., 2002; Banerjee and Iyer, 2005), the fact that mobility responds strongly up to the first acre and only weakly thereafter is, ex ante, far from obvious. The patterns are especially striking given how poor and vulnerable even marginal landowners tend to be. As appendix table 10 shows, daily per-capita consumption among the marginally landed and the landless is very similar—both slightly under two dollars a day, mean daily per-capita consumption is \$1.81 among the landless and \$1.94 among the marginally landed, a 7.6% gap. However mobility gaps between these two groups are as high as 15 percentage points depending on the measure and the state. In the poorest states—UP and Bihar—the IM^1 (primary school mobility) gap is roughly 10.3 and 15.1 percentage points respectively after netting out fixed effects.

The corresponding IM^2 gap for the two states is roughly 10.1 and 14.5 percentage points, respectively, after netting out fixed effects. These estimates are sizeable. In UP, they imply that children of marginal landowners are about 20% more likely to gain primary education or more, and 33% more likely to

[13] Asher et al. (2024), using data from the Indian Human Development Survey (IHDS), report cohabitation rates upwards of 90% till age 18, for boys and girls followed by a sharp decline, steeper for girls than for boys, likely due to marriage and patrilocality.

[14] The only exception being Tamil Nadu where for IM^1 we see some saturation.

attain middle schooling or more, vis-a-vis children of landless parents, conditional on parents having no education. [15]. In Bihar, children of marginally landed parents are 36% more likely to attain primary schooling and 72% more likely to attain middle schooling compared to children of landless parents. In West Bengal, Punjab, Maharashtra and Karnataka the corresponding likelihood increases from marginal land ownership are 14%, 9.3%, 7.5% and 3.6% for primary school attainment and 32%, 28%, 14.5% and 8.3% for middle school attainment respectively. In fact, across most states the sharp jump in mobility likelihood is already apparent among submarginal households with land wealth below an acre.

On the other hand, the mobility gaps between marginal and large landowners across these seven states is modest. The IM^1 gap between large landholders and marginal landholders is the largest in Punjab at 7 percentage points percentage points and the lowest in Bihar at 0.1 percentage points. Consistent across measures and states is the fact that intensive margin mobility gaps after an acre of land are either minimal, or are dwarfed by the intensive margin jumps. This finding is especially puzzling for two reasons. First, per capita consumption among large landowners is 36% higher than among marginal or submarginal landowners (appendix table 10); and second, observed mobility probabilities remain well below the 100% upper bound, leaving ample room, at least in principle, for additional land wealth to translate into further gains in human capital and mobility. A plateau in the mobility-land wealth relationship would be surprising if after the first acre the probability of upward mobility were near 100%, but this is far from true, especially in UP and Bihar and across all states for middle school mobility. To ensure that our findings are not sensitive to the choice of land ownership categories, we also show bin-scatter plots of IM^1 and IM^2 over the land distribution, with and without the fixed effects in equation 3 shown in appendix figures 10 and 11. We see the same step and plateau pattern as in figure 2.

The robustness of our findings to village and caste fixed effects is worth emphasizing. On caste, one might conjecture that landlessness and low access or demand for schooling are jointly determined by caste identity. If so, changes in mobility with land would simply reflect changes in caste composition across land classes. According to the summary statistics in appendix table 10, Scheduled Caste (SC) households are indeed much more likely to be landless. However, our estimates are robust to the inclusion of *caste* fixed effects, so within-caste comparisons still display the same extensive-margin gap; if caste rather than land were the operative mechanism, adding caste fixed effects would materially attenuate the extensive-margin difference, which it does not. With village fixed effects in place, we constrain our comparison to households that have access to similar schools, infrastructure, and a host of shared environmental and agro-climatic conditions. In tandem with the fact that permanent migration rates in rural India are very low (Munshi and Rosenzweig, 2016), village fixed effects are a reasonable way to match on shared histories of access and exposure to these factors. Our results remain unchanged after including village fixed effects. This suggests that access/sorting and identity that could differ systematically between landed and landless households, are not driving the results. We will return to these lines of inquiry when ruling out alternative explanation in section 5.6 of the paper.

[15] Percentage gain computed as $\frac{\hat{\beta}_{\text{marginal}}}{I\bar{M}^k_{L=\text{landless}}}$, where $k \in \{1,2\}$ and $I\bar{M}^k_{L=\text{landless}}$ is the raw average among the landless.

Finally, heterogeneities in results across states are important to note. First, the levels of educational mobility for the landless and landed differ significantly between states. In Bihar, only 34% of children from landless families will be upwardly mobile, the same figure for Maharashtra is 88%. We also see that three states depart from the step-function trend; Rajasthan and Madhya Pradesh exhibit a much more gradual increase in the land-mobility relationship, while in Kerala we see little to no effect of land ownership on mobility, as the probability of mobility is at or above 90% across the land distribution for either measure. We will address the question of rationalizing these heterogeneities in the mechanism section of the paper.

The centrality of the extensive margin raises two natural questions. First, is the landlessness–mobility relationship *causal*? Second, if it is causal, through which mechanisms does even a small plot of land translate into higher mobility? We answer these questions in the sections that follow, beginning with causal inference.

4 Causality

The robustness of our findings to alternative specifications and their consistency across states, while intriguing, does not demonstrate causality between landlessness and mobility. The core concern that our specifications are unable to address is selection into landlessness. One might conjecture that it is unobserved heterogeneity in ability or skill, correlated across members of a household, that jointly determine why some individuals acquire and own land and others don't, whilst simultaneously determining the ability or inability of their offspring to do well in school and be more upwardly mobile. One might also worry, that low ability households are more likely to lose land through distress sales in the event of shocks, and it is this low ability draw that explains why their children do poorly in school. Although this concern is in part addressed by the established understanding of how illiquid land markets in rural India are and the primacy of inheritance in determining land ownership (Foster and Rosenzweig (2017); Deininger et al. (2009); Binswanger et al. (1995)), it warrants further consideration. The extent of land market activity varies considerably by state and distress sales are not uncommon,making selection a legitimate concern. To address this, we go further than the existing literature on land in India and tackle the issue of identification explicitly.

To demonstrate causality, we turn to a historical experiment rooted in British era land tenure policies. Specifically, we exploit a historical policy discontinuity on the western edge of the state of Maharashtra. The administrative border that today separates districts of *Ratnagiri* and *Raigad* (which lie in the Konkan administrative division) from the Deccan-plateau districts of *Pune* and *Satara* (see Figure 3) coincides with an interesting policy discontinuity. Under British rule, districts on either side of this line were placed under distinct land tenure regimes, generating sharp, persistent differences in landlessness today. We use this discontinuity to causally identify the relationship between landlessness and mobility. We begin our analysis by providing some historical context.

(a) β's from Eq 3 for IM1 (b) IM1 Raw Means (c) β's from Eq 3 for IM2 (d) IM2 Raw Means

Uttar Pradesh

Bihar

Maharashtra

West Bengal

Punjab

Karnataka

Tamil Nadu

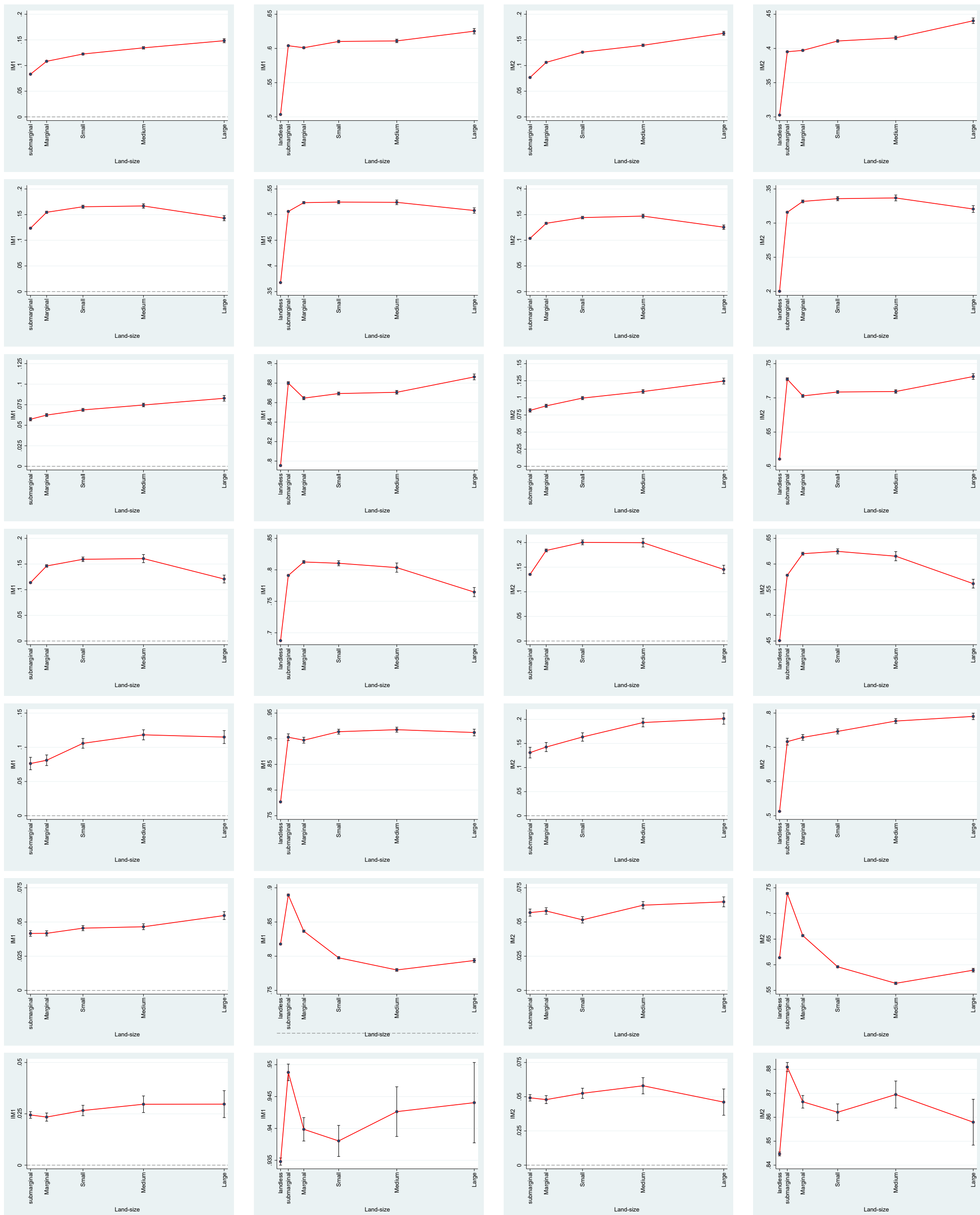
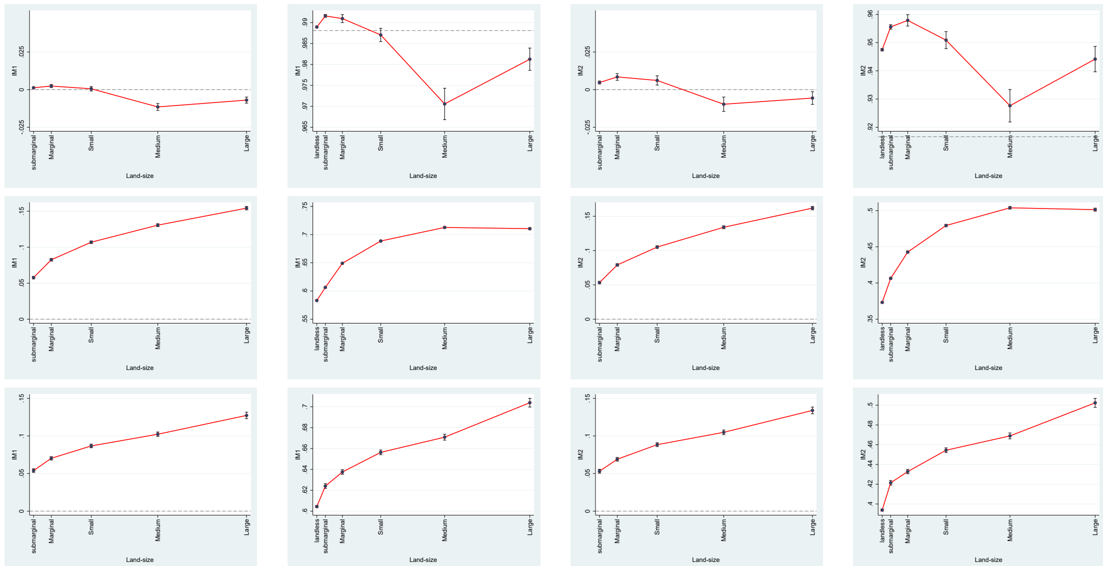


Figure 2: Mobility over the land distribution by state.

(a) β's from Eq 3 for IM1 **(b) IM1 Raw Means** **(c) β's from Eq 3 for IM2** **(d) IM2 Raw Means**



Kerala

Rajasthan

Madhya Pradesh

Figure 2: Mobility over the land distribution by state continued.

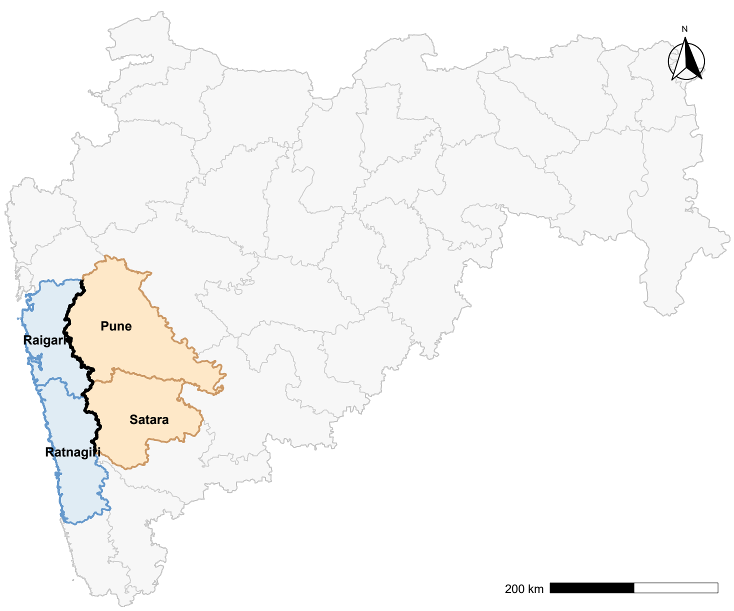


Figure 3: Study setting in Maharashtra. The map highlights the Konkan districts (Ratnagiri, Raigad) and the Deccan districts (Pune, Satara) used in our regression discontinuity design. The thick line marks the shared administrative boundary used as the RD cutoff; the 20 km band around it is the RD window.

4.1 The Historical Experiment

The British East India Company took control of much of modern Maharashtra from the Maratha Empire after the Anglo-Maratha War of 1817-19. As British administrators began governing the region, they faced the fiscally important and politically sensitive issue of taking over and reforming the existing land tenure and taxation system [16]. They inherited a patchwork of tenure and revenue contracts that varied in *who* the state recognized as the revenue unit and *how* claims over cultivation were organized. The two predominant types were:

- Ryotwari (cultivator-based): assessment of land revenues and responsibility to pay rested with the individual cultivator the (*ryot*); ryots were typically small farmers with cultivation and occupancy rights to the land they cultivated. Under Ryotwari, occupancy was relatively secure conditional on revenue payment (to the state); transfers and mortgages of rights were feasible and increasingly codified.[17]
- Intermediated/Zamindari tenures: the state recognized an intermediary revenue farmer—called the *khot* in the Konkan and the *Patil* in the Deccan—at the village or multi-village level; cultivators paid rent/cesses to the intermediary, who in turn was responsible for land revenue and local dues. Intermediaries typically influenced occupancy renewal, transfers, enjoyed de facto property rights over the land, and extracted surplus profit beyond revenue. They could evict cultivators for not paying dues and were regarded local chiefs[18].

British policy in the region articulated a preference to settle directly with cultivators where feasible (Ryotwari), but to accommodate deeply embedded intermediation where dismantling it risked disorder and disruption of revenue collection. This risk was especially salient for the Konkan region lying in Ratnagiri and Kolaba (now Raigad) districts, given the influence and control the Khots enjoyed over the highly fertile and profitable western coast of the Konkan. British administrators recognized that disrupting *Khoti* intermediation could be extremely problematic for revenue collection given the organization of the *Khots* and the sizeable contribution the coastal belt made to British revenue [19]. Thus, in practice, administrators implemented a policy discontinuity: a broad roll-out of Ryotwari and abolishment of intermediaries (*Patils*) across the Deccan, including the entirety of Pune and Satara, and a de facto maintenance of *Khoti* intermediation across Ratnagiri and Raigad districts of the Konkan administrative division (including through the 1820s–30s), later *formalized* by the *Khoti Settlement Act, 1880* (Bombay Act I of 1880)[20]. In summary, the Konkan–Deccan line is not just cartographic; it marks (for the districts mentioned above) a sharp divide in land tenure systems. By raising extraction at small scales, weakening transferability of rights, and increasing tenancy insecurity, *Khoti* made it harder for marginal cultivators to retain plots across shocks and transitions

[16] Land Revenue i.e. taxation on agricultural land was roughly 60% of total tax revenue collected by the British and accounted for about half of total revenue (Banerjee and Iyer, 2005; Kumar, 1983).

[17] Classic overviews for Bombay Deccan in Choksey (1961); comparative perspective in Charlesworth (1985).

[18] Institutional descriptions and district coverage in Charlesworth (1985); Government of Maharashtra (iousb,i). On practice and conflict, see Suradkar (2013).

[19] See Kaiwar (1994) for a political-economy perspective on how intermediation shaped surplus claims revenue collection.

[20] On the move toward Ryotwari in the Deccan, see Choksey (1961). On the Konkan exception and its regularization, see Charlesworth (1985) and the statutory text of the *Khoti Settlement Act, 1880* (Kho, 1880). District-level summaries and later abolition are in the Maharashtra gazetteers (Government of Maharashtra, iousb,i); Ambedkar's 1937 speech on a bill to abolish *Khoti* documents the regime's footprint and rationale for abolition (Ambedkar, 1979).

and allowed arbitrary removal of ryots per the will of the *Khot*; Ryotwari on the other hand made retention relatively easier. Khoti intermediation was abolished by the Maharashtra state government, now a part of the independent Indian government, under the *Maharashtra Khoti Abolition Act* of 1950. This act was part of a larger set of legislative actions which, in addition to abolishing intermediaries, also granted formal ownership and property rights to cultivators and tenants across the state under the *Hyderabad Tenancy & Agricultural Lands Act, 1950* and the *Bombay Tenancy & Agricultural Lands Act, 1958*[21]. In doing so, government policy ossified the discontinuity in tenure rights and status, into a discontinuity in formal ownership rights. The existence of Khoti for an additional 130 years vis-a-vis intermediation tenures in regions outside the Konkan, together with state policy of granting ownership rights to tenants in the 1950's, imply a higher steady-state *prevalence of landlessness* on the Konkan side than just across the border. In the sections that follow, we document the persistent effects of this historical experiment in producing a sharp discontinuity in landlessness across the Konkan–Deccan border today. It is this discontinuity that we use as our source of identification.

This experiment has some clear advantages in enabling causal inference. First, by rooting higher landlessness just inside the Konkan side of the border in a policy discontinuity dating back to the early 1820's, the experiment helps us plausibly get around the issue of selection into landlessness. That is, households on the Konkan side of the border are more likely to be landless since their members are more likely to be born into landlessness, which is a result of the legacy of tenure insecurity, extraction, and eviction experienced by previous generations. It is the accident of birth on the "wrong" side of the border that makes it discontinuously more likely for parents and household heads to be landless, not discontinuously lower ability or skill that could jointly explain their landlessness and the inability of their children to do well in school. Landlessness is explained by historical factors —the British administrations political calculus underlying the policy discontinuity— which are plausibly exogenous to potential outcomes (educational mobility) today. Another advantage is that the land tenure and revenue systems implemented by the British departed with the British in 1947 and Khoti intermediation was abolished in 1950, several decades before our outcomes are measured. Agriculture is no longer taxed by the state and the descendants of Khots do not have power of extraction and eviction over other households. Therefore, the relevant institutional differences have not been directly at play for over 61 years by the time our outcomes are measured in 2011. Finally, the nature of variation we use, highly localized, within state, also helps ensure common policy and institutional exposure pertaining to certain poverty alleviation programs and broader agricultural policy, that are funded and implemented by state governments, common access to agricultural markets, land markets, a shared macroeconomic environment, similar development levels, language, culture, and common exposure to droughts, crop failures, and other geographically determined shocks, which may affect potential outcomes.

With this institutional and historical context in place, we turn next to the econometrics of our design.

[21]See Besley and Burgess (2000) for a broader review of land reforms after independence in India.

4.2 Design and Econometric Specification

We exploit the historical tenure discontinuity described above to implement a spatial fuzzy regression discontinuity (RD) design on the Konkan-Deccan border. We implement our design on the set of villages in Ratnagiri, Raigad (Konkan side), Pune and Satara (Deccan side) that are within 20 kilometers of the contemporary border, see the appendix for details on how we construct the sample. Let X_v denote the signed distance (km) from village v to the Konkan–Deccan boundary, our forcing variable, (positive inside Konkan). For a household i in village v, let T_{iv} be the treatment dummy for being inside the Konkan where $T_{iv} = \mathbf{1}\{X_v \geq 0\}$ for all households in villages in Raigad and Ratnagiri. Let $D_{iv} \in \{0,1\}$ be a landlessness indicator, i.e $D_{iv} = 1$ if a household i in village v is landless, and 0 otherwise, and let Y_{iv} be the mobility measures defined above at the father-child pair level. We employ a fuzzy design to account for the fact that treatment compliance is imperfect, it is not the case that everyone on the Konkan side of the border is landless. Similarly, landlessness occurs on the Deccan side of the border. Formally, it is the case that for several units $D_{iv}(T_{iv} = 1) = 0$ and that $D_{iv}(T_{iv} = 0) = 1$. We estimate local linear regressions with side-specific slopes following Cattaneo et al. (2023) [22]

$$Y_{iv} = \alpha_Y + \tau_Y T_{iv} + \beta_Y X_v + \delta_Y X_v Z_v + \gamma_Y^\top G_{iv} + \varepsilon_{iv}, \tag{4}$$

$$D_{iv} = \alpha_D + \tau_D T_{iv} + \beta_D X_v + \delta_D X_v Z_v + \gamma_D^\top G_{iv} + \nu_{iv}, \tag{5}$$

where G_{iv} are controls for geography, demography and household characteristics [23]. τ_Y and τ_D denote the reduced-form and first-stage discontinuities from (4)–(5). The estimand of interest is the fuzzy-RD Wald parameter

$$\tau_{\text{FRD}} \equiv \frac{\tau_Y}{\tau_D},$$

which identifies the local average treatment effect of landlessness for compliers at the boundary given the existence of a first stage ($\tau_D \neq 0$), and assuming potential outcomes are continuous at the cutoff. Formally;

$$\begin{aligned}
\lim_{x\downarrow 0} \mathbb{E}[D_{iv}(1) \mid X_v = x] &= \lim_{x\uparrow 0} \mathbb{E}[D_{iv}(1) \mid X_v = x],\\
\lim_{x\downarrow 0} \mathbb{E}[D_{iv}(0) \mid X_v = x] &= \lim_{x\uparrow 0} \mathbb{E}[D_{iv}(0) \mid X_v = x],\\
\lim_{x\downarrow 0} \mathbb{E}[Y_{iv}(1, D_{iv}(1)) \mid X_v = x] &= \lim_{x\uparrow 0} \mathbb{E}[Y_{iv}(1, D_{iv}(1)) \mid X_v = x],\\
\lim_{x\downarrow 0} \mathbb{E}[Y_{iv}(0, D_{iv}(0)) \mid X_v = x] &= \lim_{x\uparrow 0} \mathbb{E}[Y_{iv}(0, D_{iv}(0)) \mid X_v = x].
\end{aligned}$$

In the sections that follow, we show the existence of our first stage, continuity of observables (balance checks), our main results, their robustness, and discuss potential threats to identification.

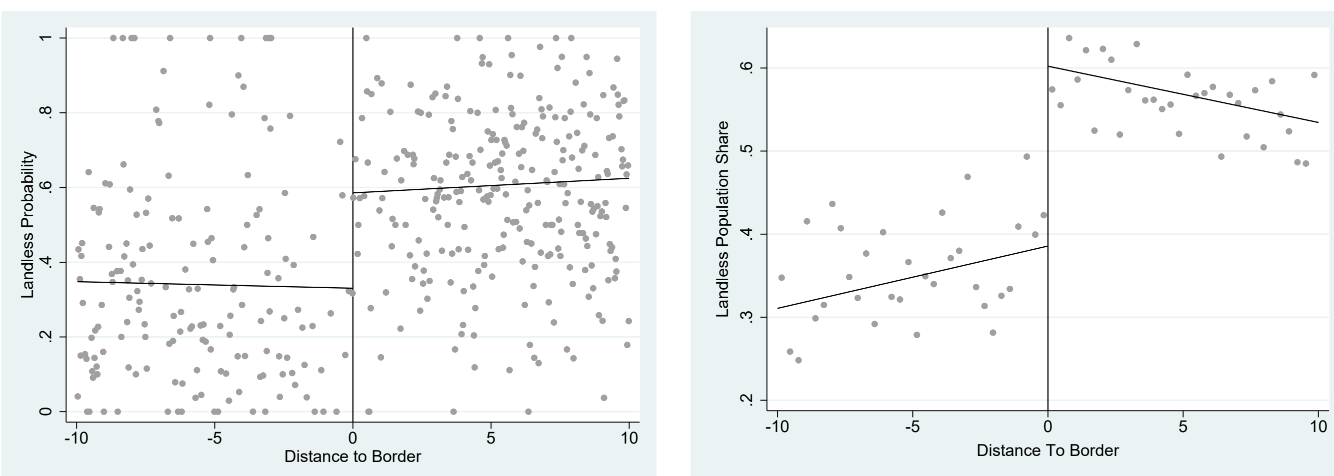
[22] Results are reported for Calonico et al. (2014) (CCT) optimal bandwidths with triangular kernel.

[23] Elevation, terrain ruggedness, long-run rainfall, population shares by age and caste, childrens age fathers age etc.

4.3 First Stage and Balance Checks

In Figure 4 and Table 3, we document a sharp discontinuity in landlessness at the Konkan–Deccan boundary. (Table 2) column 1 shows that being just inside the Konkan raises the probability of being landless by 24.7 percentage points, a near 55% increase over the control mean; with geographic and demographic controls, the estimate remains large at 21.6 percentage points a 52.1% effect over the control mean. The magnitude and significance of our estimates points to the existence of a strong first stage. The discontinuity is present within caste groups as well: among general castes the jump is 12.8 percentage points without controls and 6.7 with controls; among backward castes the corresponding estimates without and with controls are 43.1 and 26.5 percentage points respectively. All effects are significant at 99%. These results suggest that the first stage exists across social groups. These patterns align with the historical narrative that tenure insecurity and extraction under *khoti* disproportionately displaced marginal cultivators into landlessness on the Konkan side of the border. At the village level, the landless population share rises by about 20 percentage points at the cutoff—an RD estimate of 0.199 —from roughly 36% just outside (Deccan) to about 56% just inside (Konkan), i.e., an increase of approximately 55.5% relative to the control mean.

Figure 4: Regression discontinuity plots: First Stage



(a) RD plot: Landlessness (Household-level)

(b) RD plot: Village level landless shares

Next, we examine balance among observables at the village level at the cutoff. Appendix table 11 shows that most characteristics are smooth at the boundary. Primary and secondary school availability, hospital and banking presence, SC population share, terrain ruggedness, and village area exhibit no discontinuity. A handful of variables do move: elevation drops by about 383 meters on the Konkan side, from a control mean of 776 m—roughly a 50 percent difference. Middle-school availability rises by about 0.42 per 1,000 population, relative to a control mean of 0.64 (≈ 65 percent). Population density is modestly higher by 0.22 people per square kilometer, about 5 percent over the control mean of 4.52. The SC share is flat. The share under age 20 is lower by 4.7 percentage points, about 16 percent below the control mean of 30 percent. These imbalances are limited and align with known geographic imbalances of moving from mountain foothills to a plateau (elevation). Differences in public-goods

Table 2: First stage household level

	Landless						Average plot size	
	All		General castes		Backward castes			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RD estimate	0.247***	0.216***	0.128***	0.066***	0.431***	0.265***	1.584***	1.513***
	(0.011)	(0.011)	(0.017)	(0.016)	(0.017)	(0.016)	(0.104)	(0.108)
Control mean	0.42	0.42	0.40	0.40	0.43	0.43	1.8	1.8
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Observations	9561	9304	6974	6740	2450	2429	4448	4349

Notes: Local linear RD on either side of the Konkan–Deccan border (Raigad/Raigarh, Pune, Satara, Ratnagiri), estimated at the household level. Controls include distance to nearest city, village population shares (e.g., SC), terrain ruggedness, elevation, village area, and forest share. Backward castes are Scheduled Castes and Scheduled Tribes. Average plot size columns restrict to landed households with land size in acres. Robust standard errors in parentheses. $^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$.

Table 3: First stage village level and RD estimates for land inequality outcomes

	Landlessness & Inequality			Top shares (%)		
	Landless share	Gini (total land)	Gini (landed only)	Top 10	Top 5	Top 1
RD estimate	0.199***	0.138***	0.055*	–0.013	–0.009	0.006
	(0.037)	(0.028)	(0.023)	(0.040)	(0.039)	(0.022)
Control mean	0.365	0.64	0.44	0.44	0.31	0.11
Controls	YES	YES	YES	YES	YES	YES
Observations	812	796	788	796	796	796

Notes: Local linear RD on either side of the Konkan–Deccan border (Raigad/Raigarh, Pune, Satara, Ratnagiri), estimated at the village level. Controls include distance to nearest city, village population shares (e.g., SC), terrain ruggedness, elevation, village area, and forest share. Top shares are the share of land owned by the 10 biggest, 5 biggest and biggest land owner at the village level . $^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$.

availability and demography are modest, and in the results that follow, we show that our main findings are robust to controlling for geography and demographics.

4.4 Main Results

We now present our main results. Table 4 shows a clear discontinuity in children's in mobility probability at the boundary and a sizeable LATE. Reduced form results in row 1 column 1 of table 4, reported without controls, suggest that being just inside the Konkan lowers the probability of primary school mobility (IM^1) by about 2.8 percentage points and middle school mobility (IM^2) by 1.3 percentage points. (column 2) although the IM^2 result is not significant. With infrastructure, geographic and demographic controls (columns 3 and 4), the effects remain negative and similar in magnitude, 2.5 percentage point lower IM^1 (significant at 95%) and 1.1 percentage points lower IM^2 which is statistically significant 99%. The increased precision of the middle school mobility effect probably arises because we control for middle school presence, which is higher in the Konkan. Row 2 of Table 4 reports the fuzzy RD estimates with the landlessness dummy D_{iv} as the treatment. These estimates are the LATE's, i.e. τ_{FRD}, our object of interest. They capture the effect of landlessness on educational mobility for compliers, that is for units whose treatment status is switched to being landless (treated) by being on the Konkan side of the border. Reported without controls, the results indicate a statistically significant treatment effect of -11.7 percentage points with a control mean of 87 percentage points for IM^1. Thus, landlessness reduces primary school mobility by 13. 4%. With controls, the effects become larger with a treatment effect of 14.3 percentage points, implying a causal effect of 16.4% lower mobility among the landless. For IM^2 the corresponding LATEs are -3.2 percentage points without controls, which is insignificant and 7.2 percentage points, with controls and highly significant, implying a causal effect of 10.3% lower middle school mobility due to landlessness. In line with the reduced form, the FRD estimates point to economically meaningful declines in schooling mobility associated with landlessness at the boundary. In short, both the reduced-form jump and the LATE point to a sizeable causal effect of landlessness on children's educational mobility.

4.5 Robustness and Threats To Identification

Our identification hinges on the exclusion restriction: the Konkan–Deccan border affects potential outcomes only through a discontinuous shift in the probability of being landless, not through other channels. A first-order concern is that the historical tenure line could shift a broader 'bundle', government, infrastructure provision, elite control over labor markets or network strength, so that being landless just inside the Konkan is not comparable to being landless just outside. Although we show balance at the border on a range of infrastructure variables, we do not observe several potentially relevant inputs (agrarian wages, school quality, panchayat investments).

To probe this, we examine how a range of outcomes among the landless change across the border. We treat landless only RD as *descriptive diagnostics* rather than causal effects (since landless status is post-treatment). If the border induced a systematically different bundle of outcomes among the landless, proximate measures of living-standards should jump at the cutoff. Appendix Table 12 reports reduced-form RD estimates among the landless for income bands, dwelling materials, asset ownership, and enterprise status (SECC). On housing, landless households on the Konkan side are 6.5 p.p. more likely to reside in *pucca* dwellings (brick/cement/steel) relative to landless households on the Deccan side (control mean $\approx$ 34%). We see little difference in the income of the household's highest earner across the border: Konkan-side landless are weakly more likely to be in the top and bottom bands (each $\approx$ 1.6 p.p., not statistically significant) and weakly less likely to be in the middle band, suggesting at most a slightly more bimodal distribution of earnings. Among assets, landless households in the Konkan are less likely to own refrigerators and more likely to own vehicles (about -10.8 p.p. and +5.5 p.p., respectively). They are more likely to have a tax-paying salaried job in the household, and no less likely to operate a non-agricultural enterprise; in levels, such enterprises are rare and roughly 80% of landless households on both sides report agriculture as the main income source.

Taken together, these patterns show no *systematic* discontinuities in living-standards proxies that would suggest a substantively different meaning of landlessness across the border. We read the within-landless RD results as reassurance against large, unobserved shifts in what landlessness means across the border—not as identification.

Table 4: Reduced form and Fuzzy RD results on Mobility

	(1)	(2)	(3)	(4)
Reduced form (RD estimate)	-0.028^{*}	-0.013	-0.025^{*}	-0.0107^{***}
	(0.012)	(0.020)	(0.012)	(0.048)
Fuzzy RD (LATE)	-0.117^{**}	-0.032	-0.143^{*}	-0.0715^{***}
	(0.037)	(0.056)	(0.051)	(0.156)
Control mean (X<0)	0.87	0.691	0.87	0.691
Controls	NO	NO	YES	YES
Observations	17892	15853	17641	15553

Notes: Columns correspond to (1) IM^1, (2) IM^2, (3) IM^1 + *controls*, (4) IM^2 + *controls*. Reduced-form rows report RD discontinuities; fuzzy RD rows report the *robust* LATE with landlessness as the treatment. Controls include: Village level elevation, ruggedness, primary, middle, and senior school, banking and healthcare facility presence. We also control for distance to nearest cities, SC, ST, population shares, share population under 18. All specifications use local linear (p=1) RD with triangular kernel at cutoff c=0 and CCT bandwidth selection; standard errors clustered at the household level (`hhid`). $^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$.

Furthermore, as we show in the last three columns of table 3, the concern that tenure discontinuity leads to discontinuously higher land ownership and thus political and economic control in the hands of local elites is assuaged by the fact that there are no statistically significant discontinuities in the share of land owned by the largest landowners. This is additional suggestive evidence that the downstream consequences of land concentration are not at play in our setting.

Next, we show a landed-only sharp RD on mobility outcomes to explore the concern that the Konkan–Deccan line may shift measures like school quality, which we don't directly observe at the village level, that could move outcomes for everyone and, in doing so, undermine the exclusion restriction. We emphasize again that this is a post-treatment contrast since landed status itself responds to the border—so we treat this test as diagnostic, not causal. Appendix table 13 reports results. The near-zero discontinuities among the landed—both in the pooled sample and across land-size bins—are consistent with the absence of a large, common border-level shock that would depress schooling for all households irrespective of land status.

Although we cannot conclusively demonstrate exclusion, these diagnostic results help assuage concerns that a broader bundle outcomes might shift at the border and thus undermine our design.

5 Mechanisms

We now turn to mechanisms. To rationalize our findings and to uncover the mechanism underlying the step-function relationship between educational mobility and land ownership, we develop a theoretical model that endogenously delivers the step-function by combining the following key ingredients: an agrarian economy in which wages and farm productivity vary across locations; free schooling whose quality and availability are heterogeneous; child labour that equates the cost of schooling to its opportunity cost which increases with a child's age; households that weigh contemporaneous returns from child labour against the future returns to education; binding subsistence constraints on consumption; land as an income-generating asset; and complementarity in educational investments across periods.

5.1 Formalities

Households are comprised of one parent and one child, each endowed with one unit of time per period. There are two periods $t = 1, 2$, one can think of them as synonymous with early childhood or primary school years and pre-adolescence-adolescence or middle school years. Each parent is also endowed with land $T \in [0, \infty)$, parental human capital $H_p \in [0, \infty)$. The child also draws an ability shock ϵ, which is unobserved by the parent. Land T and H_p are exogenous to one another. Households live in regions R that pin down the market wage $w_R(A) > 0$ and wages can be high medium or low that is, $w_L < w_M < w_H$. Households who own some land get both wage income and land profits, $\pi(A, T)$, $\pi_T > 0$ and $\pi_{TT} < 0$, where A is just a productivity shifter. Households that do not own land receive only wage income. Children have non-zero productivity for wage work η that is strictly less than that of adults/parents, and is increasing as children grow older, that is, $0 < \eta_1 < \eta_2 < 1$. The household gets utility from per period consumption and terminal human capital of the child H, and chooses schooling efforts $e_1, e_2 \in [0, 1]$ in each period. $1 - e_t^*$ units of time are directed towards child labour. Parents supply the full unit of time to wage work. Finally, consumption in each period must satisfy subsistence, $c_t \geq \bar{c}$, where c_t is household consumption.

Formally, parents face the following problem;

$$
\begin{aligned}
\max_{e_1, e_2} \quad & u\big(c_1(e_1, T)\big) \;+\; \beta\, u\big(c_2(e_2, T)\big) \;+\; \beta^2 g\big(H(e_1, e_2, H_o, \phi)\big) \\
\text{s.t.} \quad & c_1(e_1, T) \;\leq\; w_R(A)\big[1 + \eta_1(1 - e_1)\big] + \pi(T), \qquad c_1(e_1, T) \;\geq\; \bar{c}, \\
& c_2(e_2, T) \;\leq\; w_R(A)\big[1 + \eta_2(1 - e_2)\big] + \pi(T), \qquad c_2(e_2, T) \;\geq\; \bar{c}, \\
& 0 \;\leq\; e_1, e_2 \;\leq\; 1.
\end{aligned}
$$

We assume concave utility over consumption, $u' > 0, \quad u'' \le 0$ and $u''' \ge 0$, preferences exhibit prudence. We also assume concave preferences over human capital that is, $g' \ge 0$, g: $g'' \le 0$. $0 < \beta < 1$ is the discount factor.

We assume a functional-form free human capital production function that incorporates properties of standard functions in the literature; see Attanasio et al. (2022) for a review. Specifically, let $H \equiv H_3$ be the terminal human capital level attained at the end of period 2, with the following properties: (i) each effort raises aggregate human capital, the partial derivatives of H w.r.t. e_1 and e_2 , $H_1, H_2 \ge 0$, (ii) efforts across periods exhibit complementarity, thus the cross partial $H_{12} \ge 0$. (iii) further; $H_{11}, H_{22} < 0$. (iv) $H_o = H_p^{\theta}, \quad 0 \le \theta < 1$ where H_o is the stock of human capital that the child has before starting school. $H_o = H_p^{\theta} \quad 0 \le \theta < 1$ then just means that parents pass on some human capital to their children with diminishing returns. ϕ is a vector $(\phi_1, \phi_2) \quad \& \quad \phi_1, \phi_2 \le 1$ that captures school quality; The role of school quality is to make schooling efforts more effective, specifically,

$$\frac{\partial^2 H}{\partial \phi_j \partial e_j} > 0 \tag{6}$$

To capture the fact that middle school availability is much lower than primary school availability in rural India (ASER Centre, 2019), we assume that $\varphi_1 > \varphi_2$. Embedded in our setup is the idea that parents internalize all the features of the human capital production function.

Mobility. Our model defines two mobility measures M^1 and M^2 that map to our empirical measures IM^1 and IM^2 respectively. With ability shock $\varepsilon > 0$ with fixed distribution F_ε, the child is upward mobile in M^2 if;

$$\varepsilon H^3 \ge \bar{H}_2 > H_p \tag{7}$$

and in M^1 if;

$$\varepsilon H^2 \ge \bar{H}_1 > H_p \tag{8}$$

Where H^2 is the child's stock of human capital at the end of period 1 that is;.

$$H^2 = H(e_1^*(T), H_o, \varphi) \tag{9}$$

Mobility likelihood then is;

$$\begin{aligned} M^2(T; H_p) &= 1 - F_\varepsilon\big(\varepsilon^*(T; H_p)\big), \\ \varepsilon^*(T; H_p) &= \frac{\bar{H}_2}{H\big(e_1^*(T),\, e_2^*(T),\, H_0, \varphi\big)} \end{aligned} \tag{10}$$

$$\begin{aligned} M^1(T; H_p) &= 1 - F_\varepsilon\big(\varepsilon_1^*(T; H_p)\big), \\ \varepsilon_1^*(T; H_p) &= \frac{\bar{H}_1}{H^2\big(e_1^*(T),\, H_p\big)} \end{aligned} \tag{11}$$

Where $0 < \bar{H}_1 < \bar{H}_2$ are the levels of human capital required to complete primary and middle school, respectively, and $H_p < \bar{H}_1$ is the level of parental human capital for parents who have not completed primary school. Before turning to our analysis, we make some additional assumptions.

Assumption 1. *We assume that the curvature of g and the strength of gross complementarity H_{12} are such that;*

$$g'(H)H_{12} \; > \; -g''(H)\, H_1 H_2. \tag{12}$$

Lemma 1. *Under assumption 1, the optimal policies e_1^* and e_2^* are net/strategic complements, i.e*

$$\frac{\partial e_1^*}{\partial e_2}, \frac{\partial e_2^*}{\partial e_1} > 0 \tag{13}$$

See proof.

Assumption 2. *Strict second-order conditions hold for households constrained optimization problem.*

See discussion here.

These additional assumption ensure; (i) that optimal education efforts across periods are strategic complements, that is, if parents choice of e_1^* rises then that increases the optimal e_2^*. Gross complementarity in the production function is not undone by the curvature of g and (ii) that our problem permits interior maximization such that the first-order conditions characterize a local maxima.

5.2 Analysis and Core Results

Having described model primitives, we now turn to the analysis of our model and develop the core results. We begin by describing the choice problem households with different levels of land endowment face.

For households with $T = 0$, the budgets reduce to;

$$c_1 \le w_R(A)\big[1 + \eta_1(1 - e_1)\big], \qquad c_2 \le w_R(A)\big[1 + \eta_2(1 - e_2)\big]. \tag{14}$$

In general we assume that in regions where wages are w_L, w_M, the consumption constraint always binds for the landless and so they pick e_j^* to set $c_j \ge \bar{c}$, implying;

$$e_j^* \le 1 + 1/\eta_j - \frac{\bar{c}}{w_R(A)\eta_j} \tag{15}$$

We assume that in regions with wages at most w_M, parents labour earnings alone are not enough to meet subsistence constraints, that is $\bar{c} > w_M(A)$, ensuring that $e_j^* \le 1$. In other words, in regions where parental labour earnings are insufficient to meet household subsistence constraints, parents must rely on child labour as a means to augment consumption above the threshold. Parents cannot optimally choose children's education efforts from the constrained optimization problem implied by their preferences and budgets. This feature of our theory is an extension of some of the core features of the framework put forward by Basu and Van (1998) in their seminal paper on the economics of child labour. Their analysis abstracts away from land ownership, which we explicitly incorporate. Given our framework, if wages are too low, either child labour or a certain threshold level of land wealth are needed to alleviate subsistence constraints, which brings us to Lemma 2.

Lemma 2. *Subsistence-relief threshold: If $w_R \leq w_M$ then $\exists \quad a \quad T^\star$ which satisfies;*

$$T^\star := \inf\left\{T \geq 0 : \; w_R(A)\left[1+\eta_j(1-e_j^*(T))\right]+\pi(A,T) \geq \bar{c}\right\}.$$

See proof.

Lemma 2 says that there exists a unique level of threshold land wealth that allows parents to optimally choose e_j^* from the constrained optimization problem implied by household preferences and budgets and to have household consumption above subsistence. Constrained households with land wealth $T < T^\star$ choose education efforts the same way as the landless do, and set;

$$e_j^* \leq 1+\frac{1}{\eta_j}+\frac{\pi(A,T)-\bar{c}}{w_R(A)\eta_j}. \tag{16}$$

It is straightforward to show that educational investments are increasing and thus child labour is decreasing in land wealth. In the sections that follow, we will explore the determinants of $T^\star$ and its dependence on the parameters of the environment. The key takeaway from Lemma 2 is that only unconstrained households, with either land $T > T^\star$ or all households in regions with $w = w_H$, will optimally choose e_j^*, that is, their choice of education efforts will satisfy the first order conditions from the constrained optimization;

$$\beta^2 g'(H)\, H_1 \;=\; w_R(A)\eta_1\, u'(c_1), \qquad \beta^2 g'(H)\, H_2 \;=\; w_R(A)\eta_2\, \beta\, u'(c_2) \tag{17}$$

assuming an interior optimum, see mathematical appendix for details. These households optimally weigh the contemporaneous returns to child labour against future returns to children's education, and in doing so, factor in school quality/availability, complementarity in efforts across periods, and the effect of starting human capital on optimal choices.

Our framework implies a clear regime change in the way parents make decisions about children's schooling and child labour efforts, depending on whether land-holdings are above or below threshold land. This brings us to the core propositions of our model.

Proposition 1. *Land-Mobility slope change post land wealth threshold. For regions such that $w \in \{w_L, w_M\}$, assuming consumption is non-decreasing in land ownership or that (14) and (15) hold with equality; the response of education efforts to land wealth is strictly larger when $T < T^\star$ versus $T > T^\star$;*

$$\left.\frac{de_j^*}{dT}\right|_{T<T^\star} > \left.\frac{de_j^*}{dT}\right|_{T>T^\star} \quad \Longrightarrow \quad \left.\frac{dM}{dT}\right|_{T<T^\star} > \left.\frac{dM}{dT}\right|_{T>T^\star}$$

See proof.

Proposition 1 formalizes the decision making regime change our model delivers and the change it implies in the land-mobility gradient or slope. For constrained households with land wealth below the threshold, the decision-making logic is to choose enough child labour so that subsistence is met. Any increase in land for households below $T^\star$ is passed on to alleviating subsistence constraints and leads to a one-for-one increase in children's schooling efforts producing a sharp increase in the likelihood of upward mobility as land wealth increases up to $T^\star$. On the other hand, consumption stays at or near $\bar{c}$. After $T^\star$, the change in optimal education efforts to changes in land wealth becomes more gradual as households now optimally weigh contemporaneous returns from child labour today against the future benefits of children's human capital. This produces a more gradual land-mobility gradient after $T^\star$ and increases in consumption with more land holdings.

Proposition 2. *For unconstrained households, complementarity and mild constraints on the curvature of g imply:*

$$\frac{\partial e_j^2}{\partial e_i \, \partial T} > 0.$$

Implication; *for any parameter θ:*

$$\text{if} \quad \frac{\partial e_i^*}{\partial \theta} > 0 \quad \Longrightarrow \quad \frac{\partial e_j^2}{\partial \theta \, \partial T} > 0, \qquad \text{and} \qquad \text{if} \quad \frac{\partial e_i^*}{\partial \theta} < 0 \quad \Longrightarrow \quad \frac{\partial e_j^2}{\partial \theta \, \partial T} < 0.$$

Finally, Let θ raise exactly one effort margin (e_i or e_j). Maintain: $H_{e_ie_i} < 0$, $H_{e_ie_j} \geq 0$, $\partial e_{iT}/\partial e_i < 0$, and $\partial e_{iT}/\partial e_j > 0$. $M_T \equiv \frac{\partial M}{\partial T}$

***If** θ **raises** e_i:*

$$\frac{\partial M_T}{\partial \theta} \gtrless 0 \quad \Longleftrightarrow \quad \underbrace{e_{jT} H_{e_ie_j} + H_{e_j} \frac{\partial e_{jT}}{\partial e_i}}_{\text{complementarity}} \gtrless \underbrace{|e_{iT} H_{e_ie_i}| + H_{e_i} \left| \frac{\partial e_{iT}}{\partial e_i} \right|}_{\text{own curvature}}.$$

***If** θ **lowers** e_i:*

$$\frac{\partial M_T}{\partial \theta} \lessgtr 0 \quad \Longleftrightarrow \quad e_{jT} H_{e_ie_j} + H_{e_j} \frac{\partial e_{jT}}{\partial e_i} \gtrless |e_{iT} H_{e_ie_i}| + H_{e_i} \left| \frac{\partial e_{iT}}{\partial e_i} \right|$$

Complementarity makes later effort more sensitive to land when earlier effort shifts up; a change in any parameter that raises / lowers the early margin e_i^* increases / reduces the T-gradient of later effort—and increases / reduces the T-gradient of mobility as well as long as complementarity offsets the curvature of H.

See proof.

This proposition illustrates how complementarity affects the land-mobility gradient. The intuition is as follows; suppose that an unconstrained households land wealth (exogenously) increases in period 1. This increase in wealth leads to an income increase that is optimally shared between raising consumption and raising children's education efforts. Complementarity in efforts implies that optimally increasing education efforts in period one must be complemented by increases in period two efforts in order for period 1 effort increases to efficiently map to human capital gains. However, if period 2 efforts face a bottleneck in the form of low quality/availability of middle schools or rising opportunity cost of child labour, then period 1 effort will not increase optimally in response to land wealth increases, since they wont be as efficient in producing more human capital if period 2 efforts are lowered by features of the environment. Thus, if complementarity between education effort across periods is strong and second period education efforts are constrained then the response of first period education efforts to land wealth will be muted and thus the mobility response to land wealth be muted as well, resulting in further flattening of the land-mobility gradient post $T^{\star}$.

Together, these propositions articulate the step function relationship between land and educational mobility that our model delivers.

5.3 Predictions and Empirical Tests

In this section, we empirically validate the predictions of our model. We caution that our tests are aimed at correlations and should not be read causally. However, as we will show, these correlational patterns will align closely with the predictions in our model and, in doing so, will validate the mechanisms through which our framework rationalizes the observed facts.

Proposition 1 Test: The core implication of our theory is that the land–mobility step-function relationship arises because of a similar step function relationship between land and education efforts. Time invested in education should rise sharply from no land ownership to marginal land ownership and concomitantly child labour incidence should fall sharply with land wealth up to to the first few acres of land, following which we should see little movement in either variable from additional land ownership. To operationalize the test, we estimate:

$$Y_{ihd} \;=\; \alpha \;+\; \sum_{L} \beta_L \, \mathbf{1}\{h \in L\} \;+\; \gamma X_h \;+\; \left[\delta_d + \gamma_{c(i)} + \vartheta_{f(i)} + \kappa_{o(i)}\right] \;+\; \varepsilon_i, \tag{18}$$

where Y_{ihd} is an outcome for child i in household h, and region d, X_h is a vector of household controls, $\mathbf{1}\{h \in L\}$ are indicators for the landholding classes L. We omit the landless as in equation 3 so the β_L's capture effects relative to the landless. δ_d are location fixed effects (village/district), γ_c,ϑ_f,κ_0 are caste, fathers birth cohort and childs-birth cohort fixed effects. The coefficients β_L trace the shape of the outcome–land profile relative to the landless base. We take two outcomes that map directly to the channels in the model. First, annual school days (REDS 2006), defined as the number of days children attended school in a year, as reported by parents, this is our education effort measure. Second, we use child labour incidence (NSS rounds 61,66 and 68), which is a dummy variable that takes the value 1 if a child aged 6-17 reports remunerative field/other work or household labour as their main activity.

Figure 5 plot β_L's from equation (18) for the child labour outcome and shows that the share of children engaged in work falls sharply when moving from landless to marginal landholding households and then stabilizes at higher land classes. The share of children in landless households who are engaged in child labour is about 16.5% and falls to around 8.2% for marginally landed households, a near 50% effect, with minimal effects as land wealth grows further. Figure 6 plots β_L's for the days in school outcome. The pattern is what we expect: annual school days for children rise steeply between landless and marginal landholders and level off thereafter. Taken together, these patterns align with the mechanism: land wealth increases at or around the extensive margin of the land distribution relax subsistence constraints, reducing the need for child labour and raising schooling effort until the threshold land wealth, beyond which additional land has limited marginal effect—producing a plateau in education effort and, by implication, in the mobility–land gradient. Another implication of this proposition is that below $T^\star$ households stay at or slightly above subsistence consumption with minimal gains in consumption with additional land wealth. After $T^\star$ land wealth delivers significant consumption gains. This is exactly the pattern we discussed earlier in consumption levels see table 10. Per capita consumption for marginal households is only 7.6% higher than landless households, but as land wealth increases after the first acre per capita consumption rises faster.

Proposition 2 Test: Proposition 2 implies that with complementarity, first period education effort becomes less sensitive to land when second period effort is pushed down, and thus, the mobility–land gradient after $T^\star$ flattens. We take this prediction to the data by running the following equation;

$$IM^1_{is} = \alpha + \beta_1 \mathbf{1}\{l_i \in \text{Large}\} + \beta_2 \left(\mathbf{1}\{l_i \in \text{Large}\} \times \theta_s\right) + \beta_3 \theta_s + \left[\delta_d + \gamma_{c(i)} + \vartheta_{f(i)} + \kappa_{o(i)}\right] + \varepsilon_{is}. \tag{19}$$

where IM^1_{is} is the mobility outcome for father-child pair i in subdistrict s. $[\delta_d + \gamma_c + \vartheta_f + \kappa_o]$ denote the same fixed effects as before. We run equation 19 on the subset of marginal and large land owning households, so that β_1 captures the mobility gap between the two groups. This is our measure of the mobility-land gradient. θ_s captures the parameter that exogenously moves second period efforts. In this specification, β_2 captures how the large–marginal mobility gap varies with the strength of the second-period margin.

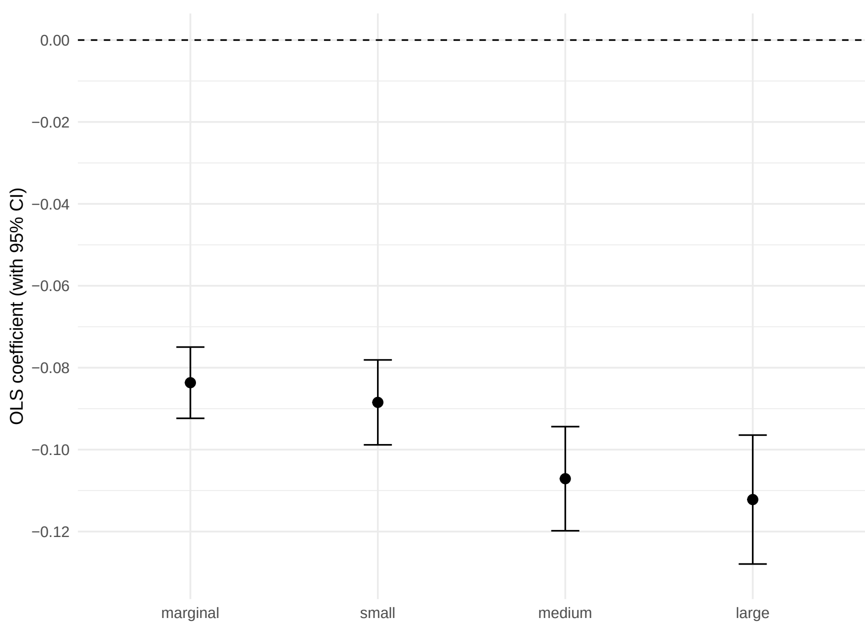


Figure 5: Child labour incidence by land class (NSS). Notes: plotted values correspond to estimated profiles across land classes; see specification (18).

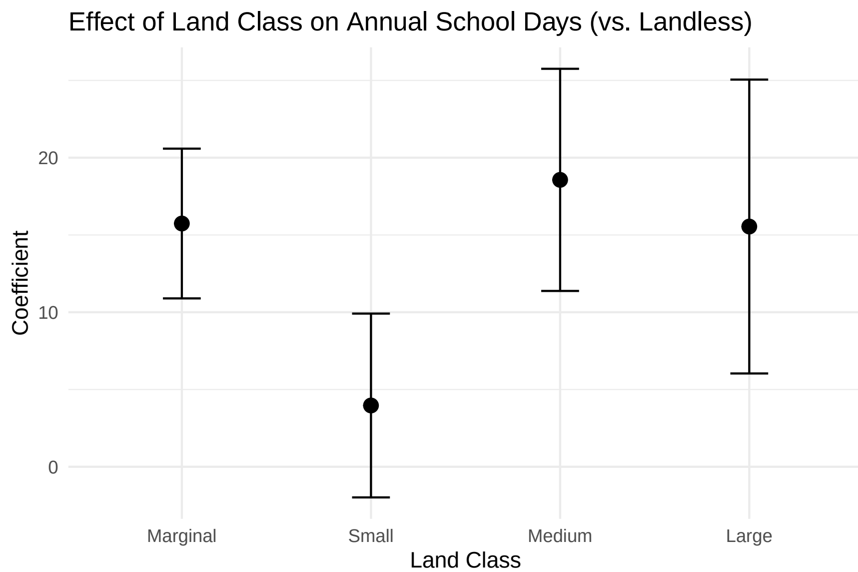


Figure 6: Annual school days by land class (REDS 2006). Notes: plotted values correspond to estimated profiles across land classes; see specification (18).

We measure $\theta \in \{\varphi_2, \eta_2\}$ at the subdistrict level. For φ_2 we use middle schools per thousand people. For η_2 we construct the subdistrict percentile in the national distribution of agro-climatic productivity for crops with substantial input of adolescent labour, wheat, sugarcane, cotton; see Bau et al. (2021) for a discussion on incidence of adolescent labour for these crops. To do so we use FAO data on predicted productivity for these crops. FAO constructs a predicted productivity measure for 44 major crops produced in India under using controlled experiments based on agro-climatic conditions at the 9.5x9.5 sq. km grid cell level. We aggregate this measure at the subdistrict level for wheat, sugarcane and cotton, take the average across the three crops for each subdistrict and then rank each subdistrict in national distribution of the measure. The resulting percentile rank is our measure of η_2. Higher η_2 implies stronger period-2 labour pull. The proposition predicts $\beta_2 > 0$ when $\theta = \varphi_2$ (more middle schools sharpen the gradient) and $\beta_2 < 0$ when $\theta = \eta_2$ (higher adolescent labour productivity flattens it). We estimate equation 19 for the seven states for which average mobility likelihood is significantly below 100%, leaving significant room for additional land wealth to map to additional mobility [24]. Table 5 reports results. Clearly, the predictions of our model bear out in the data. the estimated β_2 is positive and significant across states when $\theta = \varphi_2$. The effects suggest that a one standard deviation increase in middles school density increases the gap in IM^1 between the marginally landed and large landed by between 0.5 percentage points to as high as (Maharashtra and UP) to 2.4 percentage points in Punjab. The patterns in the data are also consistent for the prediction on η_2, with a negative β_2 across states. Estimates on η_2 are noisier and significantly smaller in magnitude compared to φ_2, the most sizeable effect being in UP where a 1 standard deviation increase in our measure of adolescent labour productivity is associated with a decrease in the marginal-large mobility gap $\approx$ 0.3 percentage points.

[24] We drop Karnataka, Tamil Nadu and Kerala since we see very little variation in middle school availability across theses states and IM^1 is quite saturated for the latter two states leaving little room for a land-mobility gradient.

Table 5: Interaction of land category with second-period environment (θ)

	MH	UP	MP	PB	RJ	BR	WB
Panel A: $\theta = \varphi_2$							
$\hat{\beta}_2$	0.00428**	0.00427*	0.0181*	0.0241*	0.0221*	0.0071*	0.0117
Panel B: $\theta = \eta_2$							
$\hat{\beta}_2$	-0.0000404	-0.00257***	-0.00153***	-0.000479*	-0.0000559	-0.000255**	-0.000879***
Observations	316,054	887,868	335,832	23,902	787,354	309,333	116,028
Fixed effects	YES	YES	YES	YES	YES	YES	YES

Notes: Each cell reports the interaction coefficient β_2 from (19) estimated on marginal vs. large landholders. Positive $\hat{\beta}_2$ for φ_2 and negative $\hat{\beta}_2$ for η_2 are the signs implied by Proposition 2. State abbreviations: MH = Maharashtra, UP= Uttar Pradesh, MP = Madhya Pradesh, PB=Punjab, RJ= Rajhastan, BR=Bihar, WB= West Bengal.
$*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

5.4 Model Predictions and State Heterogeneity

Our framework rationalizes observed heterogeneities across states. Specifically, the framework makes predictions about: (i) differences in absolute levels of mobility between states and (ii) the precise size of threshold land wealth and thus the mobility-land gradient. The former are rooted in variation in school quality while the latter is determined by differences in agricultural productivity. Proposition 3 formally states these predictions.

Proposition 3 (Heterogeneities;)**.** *(i) School quality increases mobility likelihood for all households across the land distribution;*

$$\frac{\partial M^j(T)}{\partial \varphi_j} > 0 \quad \forall \quad T \quad \& \quad j \in \{1,2\} \tag{20}$$

(ii) Higher agricultural productivity reduces the land threshold:

$$\frac{\partial T^\star}{\partial A} < 0. \tag{21}$$

See proof.

Our framework suggests that in parts of India, where school quality is better, mobility likelihood should be higher across the land distribution. In addition, in regions where land is more productive, the threshold amount of land that alleviates subsistence beyond which mobility flattens is lower.

We will proceed by validating these predictions and then discuss how they map to the differences we see across states. First, we aggregate IM^1 and IM^2 at the subdistrict level for the landed (those with at-least an acre of land) and the landless, and correlate them with various district level measures of school quality from ASER data. Specifically, we aggregate and draw from ASER data, for each district, the share of schools that offer mid-day meals, have usable blackboards across grades, and average reported teacher absenteeism. The model predicts that the coefficients on measures of school quality and wages be positive and that on the share of households denied NREGA work be negative.

Next, for each subdistrict, we estimate $T^{\star}_{sd}$. We estimate it as the level of land below which the land-mobility gradient is steep and after which the gradient flattens using a continuous hinge regression in a maximum-likelihood model as described in the appendix. We then relate these thresholds to exogenous agronomic conditions. Productivity is measured as the average predicted productivity across 44 major crops at the subdistrict level, using FAO-based agroclimatic predictors that we discussed above. For each subdistrict we take the average of the productivity measure across all 44 crops and take the log of that yield, call it A_{sd}. Higher A_{sd} indicates more productive land and thus a smaller threshold level of land to clear subsistence. The empirical prediction is a negative relationship between A_{sd} and $T^{\star}_{sd}$.

The results in Tables 6 and 7 corroborate the predictions. Across all measures of school quality, we find sizeable correlations. Higher teacher absenteeism is associated with sharp declines in mobility, a 1 standard deviation increase in teacher absenteeism, correlates with mobility probability being cut by anywhere between 21 to 26 percentage points. Higher midday meal provision and better infrastructure are associated with significant increases in mobility.

Table 6: School Quality and Intergenerational Mobility

	(1) IM1 Landless	(2) IM1 Landed	(3) IM2 Landless	(4) IM2 Landed
Teacher Absenteeism	-0.264***	-0.217***	-0.261***	-0.254***
	(0.0321)	(0.0314)	(0.0299)	(0.0340)
Usable Black Boards	0.222**	0.164*	0.227**	0.186*
	(0.0859)	(0.0835)	(0.0800)	(0.0905)
Mid-day Meals	0.191***	0.177***	0.151***	0.160***
	(0.0215)	(0.0208)	(0.0200)	(0.0226)
Observations	1,610	1,591	1,610	1,591
State Fixed Effects	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses. Each cell reports results from a regression of subdistrict level average mobility (IM^1 and IM^2) separately for the landed and the landless. The regressions controls for infrastructure (schools, hospitals, banks per-capita), geographic controls, population and demographics as well as state fixed effects.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 7: Productivity and the land threshold $T^{\star}$

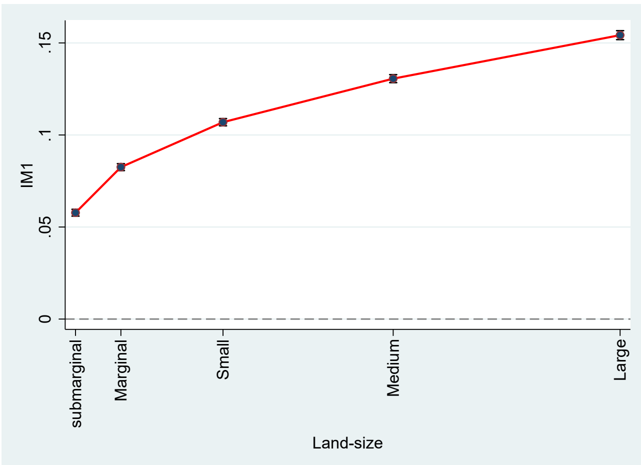
	(1)	(2)	(3)
Productivity	-2.812**	-2.762**	-1.172*
	(0.974)	(0.960)	(0.656)
Observations	1,712	1,712	1,712
Controls	No	Yes	Yes
State FE	No	No	Yes

Notes: Outcome is the estimated threshold $T^{\star}$ from the hinge–logit MLE. "Productivity" is the subdistrict measure A (average predicted crop productivity). Controls include subdistrict area, forest area share, average ruggedness and elevation. Standard errors in parentheses; $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

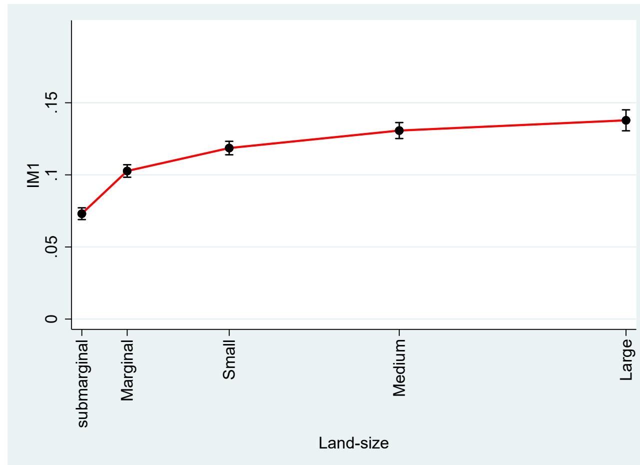
Results in table 7show that higher land productivity is associated with a significantly smaller $T^{\star}$, a 1 standard deviation in increase in productivity is associated with a 1.2 acres smaller $T^{\star}$.

These predictions and patterns in the data map directly to the heterogeneity between states. Between the mid–2000s and 2011, ASER's school quality data align with differences in mobility levels across states. Southern leaders—Kerala and Tamil Nadu—consistently exhibit lower teacher absenteeism and stronger basic infrastructure (usable blackboards, water, toilets), alongside more reliable mid-day meal provision than lower-mobility northern states like Bihar and Uttar Pradesh. By ASER-2010, meals were served on the day of visit in $\approx 83.4\%$ of government schools nationally, and $\approx 81.3\%$ reported a kitchen shed; states with long-running cooked-meal programs, Tamil Nadu, Kerala report nearly ubiquitous provision (ASER Centre, 2011). Administrative monitoring in FY2009–2011 shows stark cross-state gaps in delivery of planned meals: Rajasthan $\sim 97\%$ versus Bihar $\sim 59\%$, with Maharashtra and Punjab generally in the upper-middle of this distribution and West Bengal mixed but improving over this window (Ministry of Human Resource Development, 2011). In short low mobility states like Bihar exhibit significantly worse school quality than intermediate states like Maharashtra and West Bengal which in turn are behind states like Kerala and Tamil Nadu.

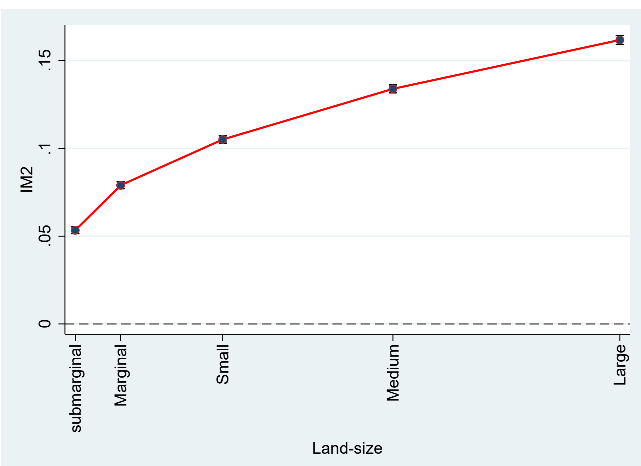
Finally, the prediction and pattern suggesting that less productive land implies higher threshold land and thus a more gradual land mobility gradient between landlessness and marginally landed, is what we see in Rajhastan. Home to the Thar desert, large parts of Rajasthan are arid and characterized by low agricultural productivity. In figure 7 we juxtapose β's from 3 for the full Rajasthan sample (figures (a) and (c)) and then for the sub-sample of low productivity districts that arent in the Thar desert ((b) and (d)). We see clearly that the much more gradual gradient between landless and marginal land owners becomes larger when looking only at higher productivity non desert districts and the plateau re-emerges, exactly as the model predicts.



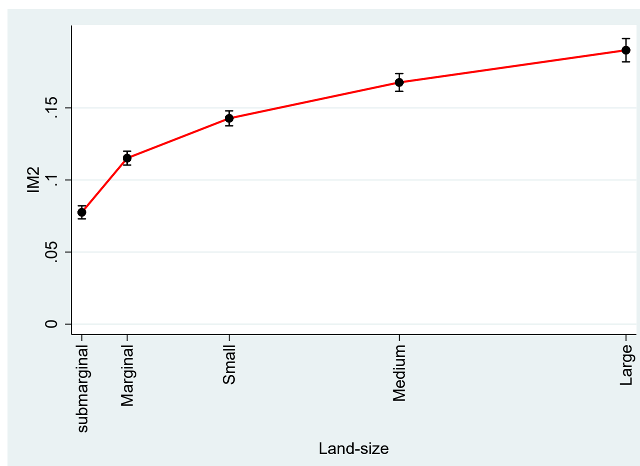
(a) β's from eq.3 Rajasthan-All Districts-IM1



(b) β's from eq.3 Rajasthan-Non-Desert Districts-IM1



(c) β's from eq.3 Rajasthan-All Districts-IM2



(d) β's from eq.3 Rajasthan-Non-Desert Districts-IM2

Figure 7: Rajasthan with and without desert districts.

5.5 Other Explanations

We now turn to alternative explanations outside our framework that could potentially explain some of the patterns in our result. In particular, explanations that can potentially explain the extensive margin gap.

The literature on poverty traps emphasizes how credit constraints hinder capital accumulation, locking households into persistently low productivity and income (Carter and Barrett, 2006). Land, in addition to its productive role is also a common source of collateral. Is the discrete mobility gap at the extensive margin a by product of the landless being unable to secure credit to shield against shocks, smooth consumption and thus maintain schooling investments? If that were the case, mobility gaps should shrink considerably where formal finance is thick. They don't. The marginal - landless mobility gap is of similar magnitude in districts with low versus high banking penetration within each state (appendix table 15). Households also borrow across the land distribution, including the landless (appendix table 14); while we see increases in credit volumes with land it is mostly driven by credit for agricultural implements, credit for household expenses does increase substantially from the landless to the landed. We do not see a pattern where credit held by the landless low or near zero followed by a discrete jump in credit for the landed that lines up with a first-acre jump in schooling. Thus, the credit mechanism does not deliver the mobility land gradient we seek to rationalize.

A second hypothesis is sorting and school-supply heterogeneity: richer (landed) households might reside in villages with better schooling infrastructure, generating a discrete mobility gap. While this could explain a level difference between the landless and the landed, it does not explain *why* mobility rises sharply up to roughly one acre and then plateaus. Direct evidence also indicates that variation in proximate measures of school quality and access is insufficient to generate our systematic pattern: Muralidharan and Kremer (2008) document that private schools in rural India have lower teacher absence, more teaching activity, much lower teacher pay, and higher test scores than government schools, yet only about 28% of the rural population lived in villages with a fee-charging private primary school in 2003, with large cross-state heterogeneity. More recently, using NSS and ASER, Kingdon (2020) reports that only 21% of children (ages 6–18) attend *private unaided* schools. That is, privately run schools that aren't funded by the government and therefore must charge fees. If differential access to high-quality private options were the dominant mechanism, states with high private penetration (e.g., Punjab) should exhibit mobility–land profiles quite unlike states with very limited private presence (e.g., Maharashtra). In contrast for most states, our results show homogeneity in the mobility-land gradient, undercutting a school-supply or sorting explanation.

Although our stylized facts and the broader pattern of results are robust to the inclusion of caste fixed effects, we push the caste identity explanation further. We estimate equation 3 for the subset households that are either SC or ST and show the estimated β's along with the estimated results for the full sample. Appendix figure 12 shows the the jump an plateau pattern *within* caste groups (columns (a) and (c)) is virtually identical to that observed for all households (columns (b) and (d)). These results strongly suggest that caste identity is not the driver of our results.

Taken together, these diagnostics are consistent with our interpretation: the extensive-margin jump reflects subsistence relief rather than shifts in credit access, sorting or caste composition.

6 Conclusion

This paper explores the importance of land ownership in shaping educational mobility in rural India. We document a novel fact. The land–mobility relationship is dominated by the extensive margin: moving from landless to roughly the first acre or less produces a large jump in children's chances of surpassing uneducated parents, while additional land beyond that yields little. This step-and-plateau pattern recurs across states despite mobility levels being well below 100%. Using a historical experiment in Maharashtra, we show that the extensive margin effect is causal, landlessness depresses upward mobility by about 10–16 percentage points.

We rationalize these findings with a simple framework in which schooling is free but uneven in quality and access, child labour is productive (especially in adolescence), households face subsistence needs, and land serves as the only income generating asset. The first acre relaxes the subsistence bind and releases time into school; beyond that threshold, extra land does not dramatically change the schooling–work trade-off unless later-stage frictions also ease. We validate these patterns in the data: large reductions in child labour and sizable gains in school time up to a small threshold level of land; muted consumption changes at the extensive margin; and post threshold slopes that flatten with lower middle-school presence and adolescent labour demand. Our framework also rationalizes the observed heterogeneities in mobility levels and the mobility-land gradient across states. In doing so we show that even plots of land significantly smaller than an acre can significantly increase the likelihood of upward mobility.

Our findings have some clear policy implications. If land primarily matters by alleviating subsistence, then providing households with a small, reliable, productive buffer can act as a powerful intervention to boost human capital. Where feasible, small-plot redistribution can be Pareto improving, atleast in the mobility and human capital sense, given how little mobility likelihood shifts with additional land after the threshold. Where land redistribution is politically constrained, policy should engineer close substitutes that mimic the same subsistence attaining function, say through predictable cash transfers and public works that smooth consumption and reduce the dependence on child labour.

Our results also shed more light on the human side of structural transformation. Recent work by Porzio et al. (2022) has shown that significant increases in human capital among recent cohorts has led to sizeable shifts in employment away from agriculture in developing societies. We highlight how the deprivation and constraints of life in an agrarian setting can constrain human capital acquisition and thus structural transformation. Our findings suggest the possibility that land redistribution might act as a catalyst for structural transformation by moving households out of deprivation, an interesting avenue for future research. Two other directions for future work are immediate. First, external validity: is the step function and centrality of the extensive margin a general feature of agrarian contexts beyond India? Systematically documenting the land-mobility relationship and its determinants across developing societies would help teach us whether subsistence and deprivation are first-order constraints in impeding human capital growth and structural transformation globally. Second, instrument choice: how should one weigh one-off redistribution against other subsistence easing policies like cash transfers and basic income guarantees? Comparative work that prices these instruments and their efficacy can help move the needle in policy debates about how best to equalize opportunity.

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Appendix

Mathematical Appendix

Lagrangian and full KKT system for unconstrained households

Households choose e_j^* by solving the constrained optimization problem.

Treat the period budgets as equalities:

$$c_1 = w_R(A)\big[1+\eta_1(1-e_1)\big]+\pi(A,T),$$
$$c_2 = w_R(A)\big[1+\eta_2(1-e_2)\big]+\pi(A,T).$$

Where, $\pi(A,0)=0$.Define inequality constraints (subsistence and effort bounds)

$$g_1 := c_1-\bar{c}\ge 0,\quad g_2 := c_2-\bar{c}\ge 0,\quad g_3 := e_1\ge 0,\ g_4 := 1-e_1\ge 0,\ g_5 := e_2\ge 0,\ g_6 := 1-e_2\ge 0.$$

Let multipliers $\mu_1,\mu_2,\lambda_1^-,\lambda_1^+,\lambda_2^-,\lambda_2^+\ge 0$ correspond to $g_1,\dots,g_6$, and θ_1,θ_2 to the two budget *equalities*. The (debt-free) Lagrangian is

$$\begin{aligned}\mathcal{L} &= u(c_1)\ +\ \beta\,u(c_2)\ +\ \beta^2\,g\big(H(e_1,e_2)\big)\\ &\quad+\mu_1(c_1-\bar{c})+\mu_2(c_2-\bar{c})+\lambda_1^-e_1+\lambda_1^+(1-e_1)+\lambda_2^-e_2+\lambda_2^+(1-e_2)\\ &\quad+\theta_1\Big(w_R(A)\big[1+\eta_1(1-e_1)\big]+\pi(A,T)-c_1\Big)+\theta_2\Big(w_R(A)\big[1+\eta_2(1-e_2)\big]+\pi(A,T)-c_2\Big).\end{aligned}\tag{22}$$

Derivatives

$$\partial_{c_1}\mathcal{L}:\quad u'(c_1)+\mu_1-\theta_1=0\ \Rightarrow\ \boxed{\theta_1=u'(c_1)+\mu_1},\tag{23}$$
$$\partial_{c_2}\mathcal{L}:\quad \beta u'(c_2)+\mu_2-\theta_2=0\ \Rightarrow\ \boxed{\theta_2=\beta u'(c_2)+\mu_2},\tag{24}$$
$$\partial_{e_1}\mathcal{L}:\quad \beta^2\,g'(H)\,H_1\ -\ \theta_1\,w_R(A)\eta_1\ +\ \lambda_1^-\ -\ \lambda_1^+\ =\ 0,\tag{25}$$
$$\partial_{e_2}\mathcal{L}:\quad \beta^2\,g'(H)\,H_2\ -\ \theta_2\,w_R(A)\eta_2\ +\ \lambda_2^-\ -\ \lambda_2^+\ =\ 0.\tag{26}$$

(Here $H_j := \partial H/\partial e_j$ and $g'(H)$ is the derivative of g evaluated at $H(e_1,e_2)$.)

Complementary slackness and feasibility.

$$\mu_t\ge 0,\quad \mu_t(c_t-\bar{c})=0\ (t=1,2),\qquad \lambda_j^{\pm}\ge 0,\quad \lambda_j^-e_j=0,\ \lambda_j^+(1-e_j)=0\ (j=1,2),\tag{27}$$
$$c_t\ge\bar{c},\qquad e_j\in[0,1],\qquad c_t=w_R(A)\big[1+\eta_t(1-e_t)\big]+\pi(A,T)\ (t=1,2).\tag{28}$$

Generalized FOCs for e_1,e_2. Substitute (23)–(24) into (25)–(26):

$$\boxed{\beta^2\,g'(H)\,H_1\ =\ w_R(A)\eta_1\big[u'(c_1)+\mu_1\big]\ -\ \lambda_1^-+\lambda_1^+},\tag{29}$$
$$\boxed{\beta^2\,g'(H)\,H_2\ =\ w_R(A)\eta_2\big[\beta u'(c_2)+\mu_2\big]\ -\ \lambda_2^-+\lambda_2^+}.\tag{30}$$

Interior simplification (no corners, no subsistence binding). If $c_t > \bar{c}$ and $e_j \in (0,1)$, then $\mu_t = \lambda_j^{\pm} = 0$ and

$$\boxed{\beta^2 \, g'(H)\, H_1 \;=\; w_R(A)\eta_1 \, u'(c_1), \qquad \beta^2 \, g'(H)\, H_2 \;=\; w_R(A)\eta_2 \, \beta \, u'(c_2)}.$$

Proof of Lemma 1

Proof. Taking the total derivative of the 1st period FOC w.r.t e_2^*;

$$\frac{\partial e_1^*}{\partial e_2} = -\frac{\beta^2 \Big[g''(H)\, H_1 H_2 \;+\; g'(H)\, H_{12} \Big]}{\beta^2 \Big[g''(H)\, H_1^2 \;+\; g'(H)\, H_{11} \Big] \;+\; (w\eta_1)^2 \, u''(c_1)}.$$

$$\boxed{\frac{\partial e_1^*}{\partial e_2} > 0 \iff \begin{cases} \beta^2 \Big[g''(H)\, H_1^2 + g'(H)\, H_{11} \Big] + (w\eta_1)^2 \, u''(c_1) \;<\; 0, \\ g''(H)\, H_1 H_2 + g'(H)\, H_{12} \;>\; 0. \end{cases}}$$

$$g'(H) > 0, \quad \frac{\partial e_1^*}{\partial e_2} > 0 \iff \begin{cases} \beta^2 \Big[g''(H)\, H_1^2 + g'(H)\, H_{11} \Big] + (w\eta_1)^2 \, u''(c_1) \;<\; 0, \\ H_{12} \;>\; -\dfrac{g''(H)}{g'(H)}\, H_1 H_2. \end{cases}$$

$$\frac{\partial e_2^*}{\partial e_1} = -\frac{\beta^2 \Big[g''(H)\, H_1 H_2 \;+\; g'(H)\, H_{12} \Big]}{\beta^2 \Big[g''(H)\, H_2^2 \;+\; g'(H)\, H_{22} \Big] \;+\; (w\eta_2)^2 \, u''(c_2)}.$$

$$\boxed{\frac{\partial e_2^*}{\partial e_1} > 0 \iff \begin{cases} \beta^2 \Big[g''(H)\, H_2^2 + g'(H)\, H_{22} \Big] + (w\eta_2)^2 \, u''(c_2) \;<\; 0, \\ g''(H)\, H_1 H_2 + g'(H)\, H_{12} \;>\; 0. \end{cases}}$$

$$g'(H) > 0, \quad \frac{\partial e_2^*}{\partial e_1} > 0 \iff \begin{cases} \beta^2 \Big[g''(H)\, H_2^2 + g'(H)\, H_{22} \Big] + (w\eta_2)^2 \, u''(c_2) \;<\; 0, \\ H_{12} \;>\; -\dfrac{g''(H)}{g'(H)}\, H_1 H_2. \end{cases}$$

$\beta^2 \Big[g''(H)\, H_2^2 + g'(H)\, H_{22} \Big] + (w\eta_2)^2 \, u''(c_2) \;<\; 0$ is true given concavity of g, u, H. $g'(H) H_{12} > -g''(H)\, H_1 H_2$. Just says that the marginal benefit of e_1 is increasing e_2. Complementarity must survive the curvature of g, i.e. the dampening effect of g'' does not offset gross complementarity which we call net complementarity. □

Proof of Lemma 2

Proof. Let

$$Y(T;A) \;=\; w_R(A)\big[1 + \eta_j\big(1 - e_j^*(T)\big)\big] + \pi(A,T), \qquad T \geq 0,$$

$$w_R(A) < \bar{c}$$

and define

$$T^\star \;:=\; \inf\{\, T \geq 0 : \; Y(T;A) \geq \bar{c}\,\}.$$

Assume: (i) $\pi(A,T)$ is non-decreasing in T with $\lim_{T\to\infty} \pi(A,T) = +\infty$; (ii) $e_j^*(T) \in [0,1]$ for all T; (iii) $Y(0;A) < \bar{c}$; and (iv) $Y(\cdot;A)$ is right–continuous.

Because $e_j^*(T) \in [0,1]$, $w_R(A)[1+\eta_j(1-e_j^*(T))]$ is bounded between $w_R(A)$ and $w_R(A)(1+\eta_j)$ for all T. Hence $Y(T;A) \to +\infty$ as $T \to \infty$. Therefore there exists $\bar{T}$ with $Y(\bar{T};A) \geq \bar{c}$, so the set $\{T \geq 0 : Y(T;A) \geq \bar{c}\}$ is nonempty and $T^\star < \infty$. By $Y(0;A) < \bar{c}$, $T^\star > 0$.

If $T < T^\star$, then by definition of the infimum $T \notin \{Y \geq \bar{c}\}$, hence $Y(T;A) < \bar{c}$.

Choose any sequence $T_n \downarrow T^\star$ with $Y(T_n;A) \geq \bar{c}$ which exists by definition of infimum. Right–continuity of $Y(\cdot;A)$ at $T^\star$ yields

$$Y(T^\star;A) \;=\; \lim_{n\to\infty} Y(T_n;A) \;\geq\; \bar{c},$$

so $T^\star$ attains subsistence. This completes the proof. □

No runaway complementarity / Strict SOC Under $u' > 0$, $u'' < 0$, $g' > 0$, $g'' \leq 0$, and for the technology $H(e_1,e_2)$ such that $H_1, H_2 > 0$ and $H_{11}, H_{22} \leq 0$ (the sign of H_{12} is unrestricted). Define first-order conditions and their derivatives:

$$F_1 := \beta^2\, g'(H)\, H_1 \;-\; w\eta_1\, u'(c_1), \tag{31}$$

$$F_2 := \beta^2\, g'(H)\, H_2 \;-\; \beta\, w\eta_2\, u'(c_2), \tag{32}$$

and

$$F_{11} := \beta^2\big[g''(H)\, H_1^2 + g'(H)\, H_{11}\big] \;+\; (w\eta_1)^2\, u''(c_1), \tag{33}$$

$$F_{22} := \beta^2\big[g''(H)\, H_2^2 + g'(H)\, H_{22}\big] \;+\; (\beta w\eta_2)^2\, u''(c_2), \tag{34}$$

$$F_{12} = F_{21} := \beta^2\big[g''(H)\, H_1 H_2 \;+\; g'(H)\, H_{12}\big]. \tag{35}$$

Discussion. Under the curvature assumptions above, $F_{11} < 0$ and $F_{22} < 0$ (own curvatures are strictly negative because $u'' < 0$ and the marginal–benefit side is weakly concave in each e_j). The Hessian of the objective with respect to (e_1,e_2) at an interior candidate is

$$\nabla^2 V \;=\; \begin{pmatrix} F_{11} & F_{12} \\ F_{12} & F_{22} \end{pmatrix}.$$

To rule out "runaway complementarity" (i.e., the cross–curvature overwhelming own concavity) and ensure a well–behaved *strict* local maximum, we impose the strict second–order condition

$$\Delta \;:=\; F_{11}F_{22} - F_{12}^2 \;>\; 0. \tag{36}$$

Equivalently, the Hessian is negative definite since $F_{11}, F_{22} < 0$. This guarantees that the joint problem is well behaved and the first–order conditions characterize a strict local optimum.

Proof of Proposition 1

Proof. We begin by deriving how optimal education efforts change with land wealth for unconstrained households. For ease of notation, we call $w \in \{w_L, w_M\}$ just w. Taking the total derivative of the FOC for e_1 and e_2 w.r.t T notice that;

$$\frac{de_1}{dT} + \frac{F_{12}}{F_{11}}\frac{de_2}{dT} = \frac{-F_{1T}}{F_{11}} \tag{37}$$

$$\frac{de_2}{dT} + \frac{F_{12}}{F_{22}}\frac{de_2}{dT} = \frac{-F_{2T}}{F_{22}} \tag{38}$$

Where, $F_{1T} = -w\eta_1 u''(c_1)\pi_T$ and $F_{1T} = -w\eta_2 u''(c_2)\pi_T$ where $\frac{\partial \pi}{\partial T} = \pi_T$. Solving (27) & (28) simultaneously yields;

$$\frac{de_1}{dT} = \frac{F_{12}\,F_{2T} - F_{22}\,F_{1T}}{\Delta} > 0 \tag{39}$$

$$\frac{de_2}{dT} = \frac{F_{12}\,F_{1T} - F_{11}\,F_{2T}}{\Delta} > 0 \tag{40}$$

Both derivatives are positive because, $F_{2T}, F_{1T} > 0$ since $u'' < 0$, $-F_{22}, -F_{11} > 0$, by assumptions 1 & 2, $F_{12} > 0$ and $\Delta > 0$.

Now notice that;

$$\left.\frac{dc_j}{dT}\right|_{T>T^\star} = \pi_T - w\eta_j\frac{de_j}{dT} \geq 0 \iff \left.\frac{\pi_T}{w\eta_j}\right|_{T>T^\star} \geq \left.\frac{de_j}{dT}\right|_{T>T^\star} \tag{41}$$

And from the choice for constrained households;

$$\left.\frac{de_j}{dT}\right|_{T<T^\star} = \left.\frac{\pi_T}{w\eta_j}\right|_{T<T^\star} \tag{42}$$

Then, concavity of π, $\pi_T\Big|_{T<T^\star} > \pi_T\Big|_{T>T^\star}$, and (31) together imply;

$$\left.\frac{de_j}{dT}\right|_{T<T^\star} = \left.\frac{\pi_T}{w\eta_j}\right|_{T<T^\star} \geq \left.\frac{de_j}{dT}\right|_{T>T^\star} \tag{43}$$

Notice that (39) holds as long as $\pi_T\Big|_{T<T^\star} \nless \pi_T\Big|_{T>T^\star}$.

Finally, since the mobility functions M^2, M^1 are monotone in H and H is monotone in e_j^*, the slope change in education efforts implies a slope the mobility-land relationship after the land threshold.

□

Proof of Proposition 2

Proof. We begin by developing the conditions under which, an increase in e_2^*, ceteris paribus, increases the response of period-1 education investments to an increase in land-wealth i.e $\frac{\partial e_1}{\partial T}$. We analyze the optimal policy $e_1^*(e_2, T)$ at an *interior* solution satisfying the FOC and SOC below. We impose throughout $w = w_R$, for ease of notation.

We know that;

$$\frac{\partial e_1}{\partial T} = \frac{w\eta_1\, u''(c_1)\, \pi_T(T)}{\beta^2\big[g''(H)H_1^2 + g'(H)H_{11}\big] + (w\eta_1)^2 u''(c_1)} \geq 0 \tag{44}$$

Since π_T does not depend on e_2^* we can write;

$$\frac{\partial^2 e_1}{\partial e_2 \partial T} = \pi_T \frac{\partial}{\partial e_2}\left[\frac{w\eta_1\, u''(c_1)}{\beta^2\big[g''(H)H_1^2 + g'(H)H_{11}\big] + (w\eta_1)^2 u''(c_1)}\right] = \pi_T \frac{\partial Z}{\partial e_2} \tag{45}$$

further since Since $\pi_T > 0$ then;

$$sign\left(\frac{\partial^2 e_1}{\partial e_2 \partial T}\right) = sign\left(\frac{\partial Z}{\partial e_2}\right) \tag{46}$$

Where, $Z = N/D$, $N = w\eta_1\, u''(c_1)$, $D = \beta^2\big[g''(H)H_1^2 + g'(H)H_{11}\big] + (w\eta_1)^2 u''(c_1)$.

Call; $\kappa = \beta^2\big[g''(H)H_1^2 + g'(H)H_{11}\big]$ and $\gamma = (w\eta_1)^2 u''(c_1)$

By quotient rule;

$$\frac{\partial Z}{\partial e_2} = \frac{N_{e_2}\, D - D_{e_2}, N}{D^2} \tag{47}$$

Where,

$$N_{e_2} = \frac{\partial N}{\partial e2} = -(w\eta_1)^2\, u'''(c_1)\, \frac{\partial e_1}{\partial e_2} < 0 \quad \left(u''' > 0, \frac{\partial e_1}{\partial e_2} > 0\right) \quad \& \quad D_{e_2} = \frac{\partial D}{\partial e_2} = \kappa_{e_2} + \gamma_{e_2}$$

assume $\frac{\partial e_1}{\partial e_2} > 0$ for now, we discuss this below.

Where $\kappa_{e_2}, \gamma_{e_2}$ are just the partials of κ and γ w.r.t. e_2 respectively. Now, notice that $N_{e_2}\, \gamma = N\, \gamma_{e_2} = -(w\eta_1)^4\, u'''(c_1) u''(c_1)\, \frac{\partial e_1}{\partial e_2}$. Applying this to (27) yields;

$$\frac{\partial Z}{\partial e_2} = \frac{N_{e_2}\, \kappa - N\, \kappa_{e_2}}{D^2} \tag{48}$$

Notice that $N_{e_2}\kappa > 0$ since $N_{e_2} < 0$ & $\kappa < 0$, also $-N > 0$, thus a sufficient condition to ensure that $\frac{\partial Z}{\partial e_2} > 0$ and thus $\frac{\partial^2 e_1}{\partial e_2 \partial T} > 0$, is that $\kappa_{e_2} \geq 0$.

Intuitively, this means that κ is non decreasing in e_2. Where κ is the rate at which the marginal benefit of e_1 declines. The interpretation is clear; as e_2 increases the benefit function of e_1 i.e. $\beta^2 g(H)$ does not become more concave in e_1; or the rate at which the marginal benefit of e_1 falls is non-increasing or minimally decreasing.

Therefore, $\kappa_{e_2} \geq 0$ and net complementarity are sufficient to secure

$$\frac{\partial^2 e_1}{\partial e_2 \partial T} > 0 \tag{49}$$

□

Proposition 4. *For unconstrained, low consumption households the substitution effect of higher child labour productivity i.e. η_2 offsets the income effect such that;* $\frac{\partial e_2^*}{\partial \eta_2} < 0$.

Proof. Take the derivative of the 2nd period FOC w.r.t η_2 and rearrange to get;

$$\frac{\partial e_2^*}{\partial \eta_2} = \underbrace{\frac{u'(c_2)\, w}{\beta(g'(H)H_{22} + g''(H)(H_{22})^2 + u''(c_2)\,(w\,\eta_2)}}_{\textit{Substitution Effect} < 0} + \underbrace{\frac{u''(c_2)\, w^2 \eta_2 (1-e_2)}{\beta(g'(H)H_{22} + g''(H)(H_{22})^2 + u''(c_2)\,(w\,\eta_2)}}_{\textit{Income Effect} > 0} \tag{50}$$

The sign then depends on the curvature of u and how high c_2 is. When c_2 is small $u'(c_2)$ is large, if the curvature of u is not too concave, then for low c_2 $u'(c_2)w - u''(c_2)w^2\eta_2(1-e_2) > 0$, implying $\frac{\partial e_2^*}{\partial \eta_2} < 0$ □

Proof of Proposition 3

Proof. Assume subsistence is slack at the relevant optima.
(A) $\partial M_j(T)/\partial \varphi_j > 0$ *for all* T.

Binding case ($T < T^*$). If the subsistence constraint binds then,
$\frac{\partial e_j^*}{\partial \varphi} = 0$ and hence

$$\frac{dH}{d\varphi} = H_\varphi \geq 0 \implies \frac{dM}{d\varphi} = M_H H_\varphi \geq 0.$$

Thus school quality is unambiguously mobility-increasing below T^*.

(ii) **Slack case ($T > T^*$).** With subsistence slack and interior FOCs

$$\beta^2 g'(H)\, H_{e_j}(e,\varphi) = \text{MC},$$

we have
$$\frac{\partial e_j^*}{\partial \varphi} = -\frac{g''(H)\,H_\varphi H_{e_j} + g'(H)\,H_{e_j\varphi}}{g''(H)\,H_{e_j}^2 + g'(H)\,H_{e_je_j}}, \qquad g'(H) > 0,\ g''(H) \le 0,$$
so
$$\frac{dH}{d\varphi} = H_\varphi + \sum_{j=1}^{2} H_{e_j}\,\frac{\partial e_j^*}{\partial \varphi}.$$

Mobility increasing: if $\dfrac{dH}{d\varphi} \ge 0$, then $\dfrac{dM}{d\varphi} = M_H\,\dfrac{dH}{d\varphi} \ge 0.$

$$D_j \equiv g''(H)\,H_{e_j}^2 + g'(H)\,H_{e_je_j} < 0, \qquad \eta_g(H) \equiv -\frac{g''(H)}{g'(H)} \ge 0.$$

$$\boxed{\frac{dH}{d\varphi} \ge 0 \iff H_\varphi + \sum_{j=1}^{2} \frac{g'(H)\,H_{e_j}}{|D_j|}\Big(H_{e_j\varphi} - \eta_g(H)\,H_\varphi\,H_{e_j}\Big) \ge 0}$$

That is school-quality is mobility increasing among households with $T > T^\star$ as long as g is not too concave in H. If g is not too concave, then $\frac{\partial e_j^*}{\partial \varphi_j}$ is either positive or small and negative. Further if $\frac{\partial e_j^*}{\partial \varphi_j} < 0$ then school quality will increase mobility among the landless by more than those with land above $T^\star$.

(B) $\partial T^\star/\partial A < 0$. Let A denote agricultural productivity and $\pi(A,T)$ farm income with $\pi_T > 0$, $\pi_{TT} < 0$, $\pi_A > 0$. Define $y(T,A,w)$ as non–child-labor resources (adult wage income plus π). Let the land threshold $T^\star$ be the minimal T at which the subsistence requirement $\bar{c}$ can be met without relying on child time (equivalently, the point where the subsistence multiplier just turns zero). Hence $T^\star$ solves

$$F(T,A) := \bar{c} - y(T,A,w) = 0, \qquad F_T = -y_T < 0, \quad F_A = -y_A < 0$$

by $\pi_T > 0$ and $\pi_A > 0$ (and adult wage income nondecreasing in A). By the implicit function theorem,

$$\frac{\partial T^\star}{\partial A} = -\frac{F_A}{F_T} = -\frac{-y_A}{-y_T} = -\frac{y_A}{y_T} < 0,$$

so higher productivity lowers the land required to clear subsistence and thus reduces $T^\star$. □

Estimating threshold Land

We estimate the kink (threshold) in the land–mobility relationship by fitting a hinge–logit model to the binary mobility outcome $Y \in \{0,1\}$ as a function of land T:

$$\Pr(Y{=}1 \mid T) = \Lambda\big(\alpha + \beta_1 T + \beta_2 (T-\tau)_+\big), \qquad (T-\tau)_+ \equiv \max\{T-\tau, 0\}, \tag{51}$$

where $\Lambda(\cdot)$ is the logistic link. The pre-kink slope is β_1 and the post-kink slope is $\beta_1 + \beta_2$. To target the step–plateau pattern we enforce (or check ex post) the shape restrictions

$$\beta_1 > 0, \qquad \beta_2 < 0. \tag{52}$$

Feasibility is ensured by requiring a minimum number of observations on both sides of any candidate threshold τ: at least $N_{\min}$ units with $T \leq \tau$ and with $T > \tau$ within the estimation cell (subdistrict).

For each subdistrict sd, the MLE is obtained over a grid of feasible thresholds. The search proceeds in two steps: (i) a coarse grid over $[q_{Lo}, q_{Hi}]$ quantiles of T (e.g. 10th–90th) subject to the feasibility rule; (ii) a fine grid refinement around the best coarse τ. The selected threshold is

$$\hat{T}^{\star}_{sd} \equiv \hat{\tau}_{sd} = \arg\max_{\tau \in \mathcal{T}_{sd}} \ell(\tau),$$

with $(\hat{\beta}_1, \hat{\beta}_2)$ re-estimated at $\hat{\tau}_{sd}$.

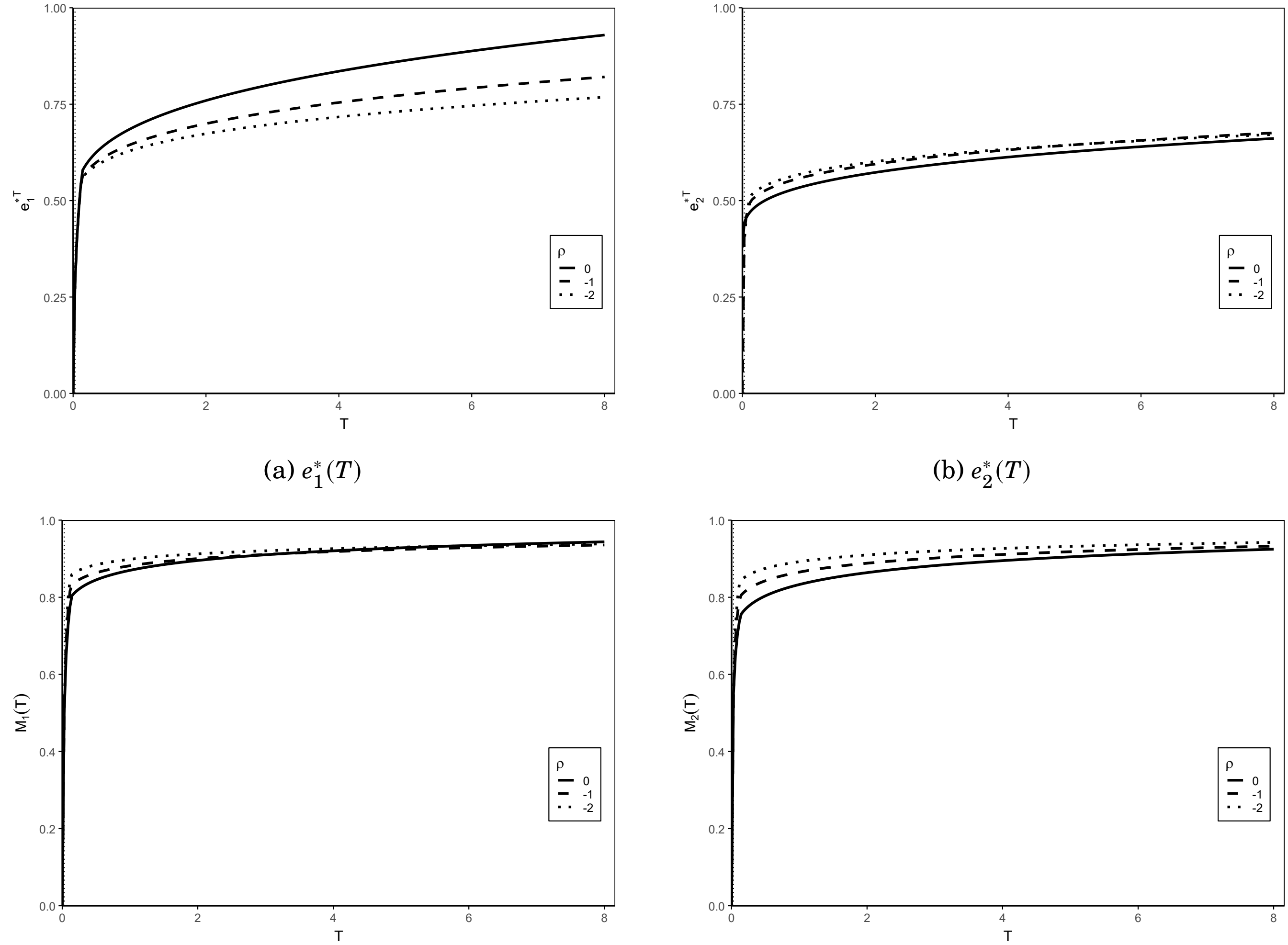
We report $\hat{T}^{\star}_{sd}$, $\hat{\beta}_1$, $\hat{\beta}_2$, and implied pre/post slopes, with robust standard errors. As a diagnostic, we compute a likelihood-ratio test against a no-kink logit ($\beta_2 = 0$) and profile-likelihood confidence intervals for τ. Results are stable to tightening $[q_{Lo}, q_{Hi}]$ and to alternative $N_{\min}$.

A Simulation Details

This section documents the functional forms, equilibrium conditions, threshold definition, and parameterization used in the simulations.

A.1 Simulations

To substantiate that our framework and the mechanisms in it deliver the step function, we present numerical simulations of our model. We develop a version of our model using conventional form and parameter assumptions, allowing some parameters to vary to show our mechanisms, see simulation appendix for details. In figure 8 we show simulation results for the optimal education efforts e_1^* in (a), e_2^* in (b) and the corresponding mobility measures in panels (c) and (d) over land wealth T. We run our simulation imposing $\eta_1 < \eta_2$, the opportunity cost of child labour is higher in period 2. To show that complementarity interacts with rising opportunity costs to flatten the education effort to land gradient and thus the mobility-land gradient, we run our simulation over different values of the complementarity parameter in the assumed CES human capital production function, ρ. More negative values of ρ imply stronger cross-period complementarity in education efforts. First notice the our model clearly delivers a sharp regime change in the response of education efforts and mobility to land wealth, with a sharp gradient at low land holdings followed by a more gradual gradient after subsistence is eased. Our simulations also show complementarity in action in Panel (a). Consistent with proposition 2, under rising opportunity cost and strong complementarity, the response of period 1 education efforts to land falls. Stronger complementarity implies a flatter e_1^*-land gradient. We see the same pattern for our mobility measures although somewhat muted. M^1 and M^2 both rise more quickly under $\rho = 0$ than under $\rho = -2$, highlighting the effect of the complementarity interaction with increasing opportunity costs.



(a) $e_1^*(T)$ (b) $e_2^*(T)$

(c) $M^1(T)$ (d) $M^2(T)$

Figure 8: Policy functions and mobility by land wealth T under varying ρ. Notes: The curves distinguish policy functions under different values of the CES complementarity parameter ρ.

Preferences and budgets. Households choose schooling efforts $e_1, e_2 \in [0,1]$ to maximize

$$\underbrace{u\big(c_1(e_1,T)\big)}_{\text{period 1 consumption}} + \beta \underbrace{u\big(c_2(e_2,T)\big)}_{\text{period 2 consumption}} + \underbrace{\beta^2 g\big(H(e_1,e_2,H_0,\phi)\big)}_{\text{terminal human capital returns}} , \tag{53}$$

subject to no-borrowing budget sets

$$c_1 \le w_R(A)\big[1+\eta_1(1-e_1)\big] + \pi(A,T), \qquad c_2 \le w_R(A)\big[1+\eta_2(1-e_2)\big] + \pi(A,T),$$

and subsistence requirements $c_1 \ge \bar{c}$, $c_2 \ge \bar{c}$. We use CRRA $u(c) = \frac{c^{1-\sigma}}{1-\sigma}$ ($\sigma > 0$), and take $g(\cdot)$ to be proportional to $\log H$ in the numerical implementation (scaled by $Q_w > 0$).

Human capital technology. Human capital is produced by a nested CES with dynamic complementarity:

$$H_1 = F(e_1, H_0) = \psi_0 + \psi_1 H_0^{\theta}, \qquad X \equiv H_2(e_1, H_0; \rho) = \Big[\lambda_1 H_1^{\rho} + (1-\lambda_1)(\phi_1 e_1)^{\rho}\Big]^{1/\rho},$$

$$H(e_1, e_2, H_0; \rho) = \Big[\lambda_2 X^{\rho} + (1-\lambda_2)(\phi_2 e_2)^{\rho}\Big]^{1/\rho},$$

where $\rho \in (-\infty, 1]$ governs curvature between components (more negative ρ implies stronger complementarity). The dynamic channel appears because X depends on e_1 and in turn raises the marginal product of e_2.

Agrarian income and subsistence threshold. Land T raises farm income via

$$\pi(A, T) = \alpha_{\pi}(AT)^{\alpha_P} \quad \text{with} \quad \alpha_P \in (0, 1),$$

capturing diminishing returns to land. The (period-1) subsistence-relief threshold is

$$T^{\star} := \inf\Big\{T \geq 0 : \; w_R(A)\big[1 + \eta_j(1 - e_j^*(T))\big] + \pi(A, T) \geq \bar{c}\Big\},$$

with $j = 1$ for the operative constraint in our baseline. In simulations $T^{\star}$ is computed as the first grid point where $c_1(T) \geq \bar{c}$.

Equilibrium conditions. Let $u'(c) = c^{-\sigma}$. The interior first-order conditions equate discounted marginal returns to effort with the opportunity cost of time through child labour:

$$\beta^2 Q_w \frac{\partial \log H}{\partial e_1} \; = \; w_R(A)\eta_1 \, u'\big(c_1(T, e_1)\big), \qquad \beta^2 Q_w \frac{\partial \log H}{\partial e_2} \; = \; \beta \, w_R(A)\eta_2 \, u'\big(c_2(T, e_2)\big).$$

When $c_1 = \bar{c}$ binds, e_1 is pinned down by $c_1(T, e_1) = \bar{c}$ (corner on the resource set), and e_2 solves the second condition given e_1.

Mobility measure. We map simulated H into an upward-mobility index using a probit-style shock:

$$M_2(T) \; = \; 1 - \Phi\left(\frac{\bar{h} - H(e_1^*(T), e_2^*(T), H_0; \rho)}{\sigma_{\varepsilon}}\right),$$

where Φ is the standard normal CDF, $\bar{h}$ is a benchmark human-capital level, and σ_{ε} is the dispersion of idiosyncratic shocks. This inherits the step/plateau features from H.

Solution method. For each ρ on a grid of T values, we: (i) test whether the subsistence constraint is slack by solving the two FOCs with a quasi-Newton method; (ii) if binding, set e_1 from $c_1 = \bar{c}$ and solve the scalar FOC for e_2 by damped Newton with a monotone line-search and a bounded grid fallback. We carry forward the last solution as the next initial guess to trace continuous policy functions $e_1^*(T), e_2^*(T)$, compute $T^{\star}$, $H(T)$, $M_2(T)$, and the numerical slope de_1/dT by central differences.

Table 8: Model parameters, meanings, values, and sources used in simulations

Parameter	Meaning	Value	Source / Justification
β	Intertemporal discount factor (stage length: life phase)	0.70	High impatience in low-income settings; cf. Laibson (1997); Haushofer and Shapiro (2016)
σ	CRRA in $u(c) = c^{1-\sigma}/(1-\sigma)$	2.00	Typical range 1–2; Hall (1988); Attanasio and Weber (1995)
$w_R(A)$	Local wage (normalized)	1.00	Normalization
η_1, η_2	Child labour opportunity cost weights	0.30, 0.90	Higher teen OC consistent with agriculture; Basu and Van (1998); International Labour Office (2017)
Q_w	Weight on terminal $\log H$ in utility	0.50	Calibration (scales H's contribution)
λ_1, λ_2	CES shares (stage 1/2)	0.40, 0.60	Calibration (skill vs. time weight)
ϕ_1, ϕ_2	Productivity shifters for e_1, e_2	1.00, 1.00	Normalization
ψ_0, ψ_1, θ	Baseline $H_1 = \psi_0 + \psi_1 H_0^{\theta}$	0.0, 0.60, 0.5	Calibration; concave inheritance channel
H_0	Parental human capital (state)	1.00	Normalization
A	Land-productivity shifter	1.00	Normalization
α_π	Profit scale in $\pi(A,T)$	0.45	Calibration
α_P	Land returns exponent in π	0.25	Diminishing returns; cf. Rosenzweig and Binswanger (1993); Foster and Rosenzweig (1995)
$\bar{c}$	Subsistence requirement per period	1.40	Calibration (matches $e_1^*(0) > 0$)
ρ	CES curvature (complementarity)	$\{-2, 0\}$	Simulation contrast: strong comp. vs. Cobb-Douglas
$\bar{h}$	Mobility benchmark in $M_2(T)$	1.00	Calibration
σ_ε	Shock dispersion in $M_2(T)$	0.35	Calibration (smooths step)

Empirical Appendix

Table 9: Taxonomy of intergenerational mobility measures

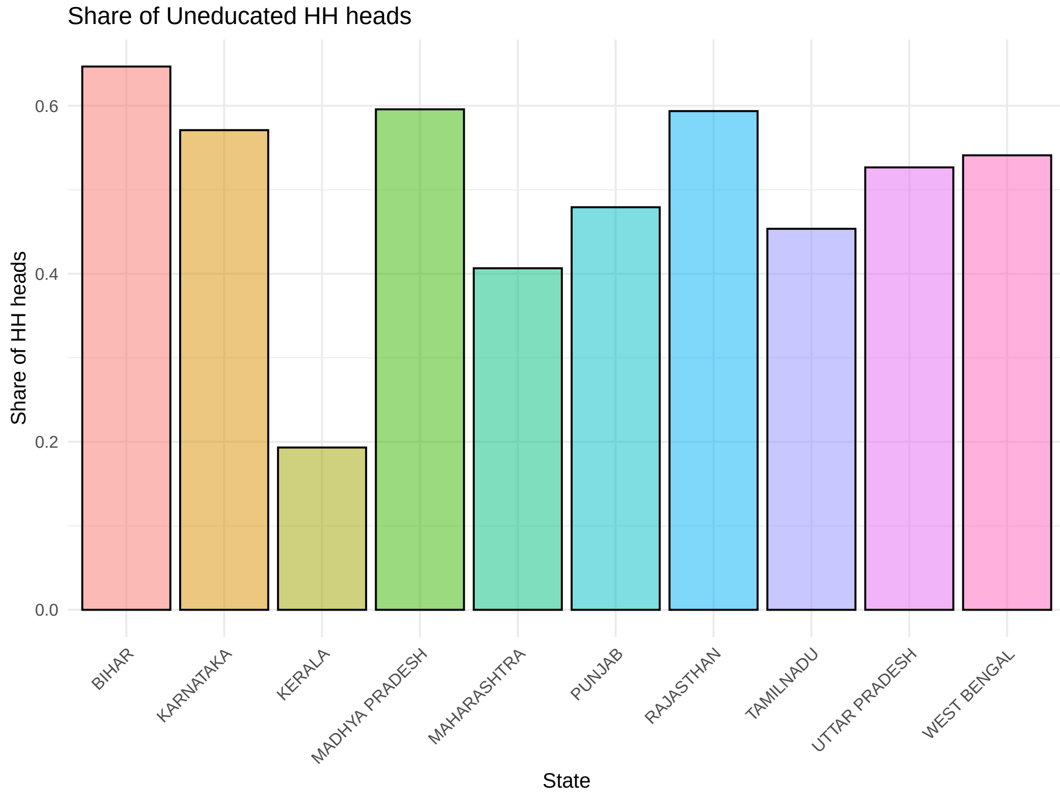
Absolute	Relative
Directional (upward-focused) • Absolute upward mobility (AUM): Pr(child level > parent level) • Mean level gain conditional on parent level • Upward transition rates across absolute thresholds	**Directional (upward-focused)** • Upward rank mobility: $\Pr(R_c > R_p)$ • Mean rank gain: $\mathbb{E}[R_c - R_p \mid R_p]$ • Upward transition rates across rank quantiles
Non-directional (exchange) • Intergenerational level correlations / variance of (child–parent) levels • Transition matrices across absolute bins with two-sided movement	**Non-directional (exchange)** • Rank–rank slope (RRS) / Spearman rank correlation • Shorrocks-type indices from rank transition matrices • Two-sided measures of re-ranking

Table 10: Summary statistics by landholding category: NSS Rounds 61, 66, 68

	Landless	Submarginal	Marginal	Small	Medium	Large
Consumption per capita (USD/day)						
	1.81	1.99	1.94	2.07	2.29	2.65
Household size						
Household size (mean)	4.27	4.72	5.03	5.43	5.81	6.51
Household size (SD)	1.95	2.06	2.21	2.53	2.76	3.58
Social group shares						
SC share	0.31	0.19	0.13	0.10	0.07	0.05
OBC share	0.41	0.38	0.38	0.37	0.37	0.39
N	60,936	57,714	39,560	23,653	14,377	10,199

Notes: Computed from NSS Rounds 61 (2004–05), 66 (2009–10), and 68 (2011–12); rural households only. Landholding categories: Landless (0), Submarginal (<0.5 ha), Marginal (0.5–1 ha), Small (1–2 ha), Medium (2–4 ha), Large (≥4 ha). Original consumption was in rupees per person per month; we convert to USD/day using a 30-day month and the single implied exchange rate of rupee 48.13 per US$, calibrated so that Landless = $1.81/day and Marginal = $1.94/day.

Figure 9: Share of Household Heads (Fathers) with $E_p = 0$



(a) β's from Eq 3 for IM1 (b) IM1 Raw Means (c) IM1 Binscatter with Fixed Effects (d) IM1 Raw Binscatter

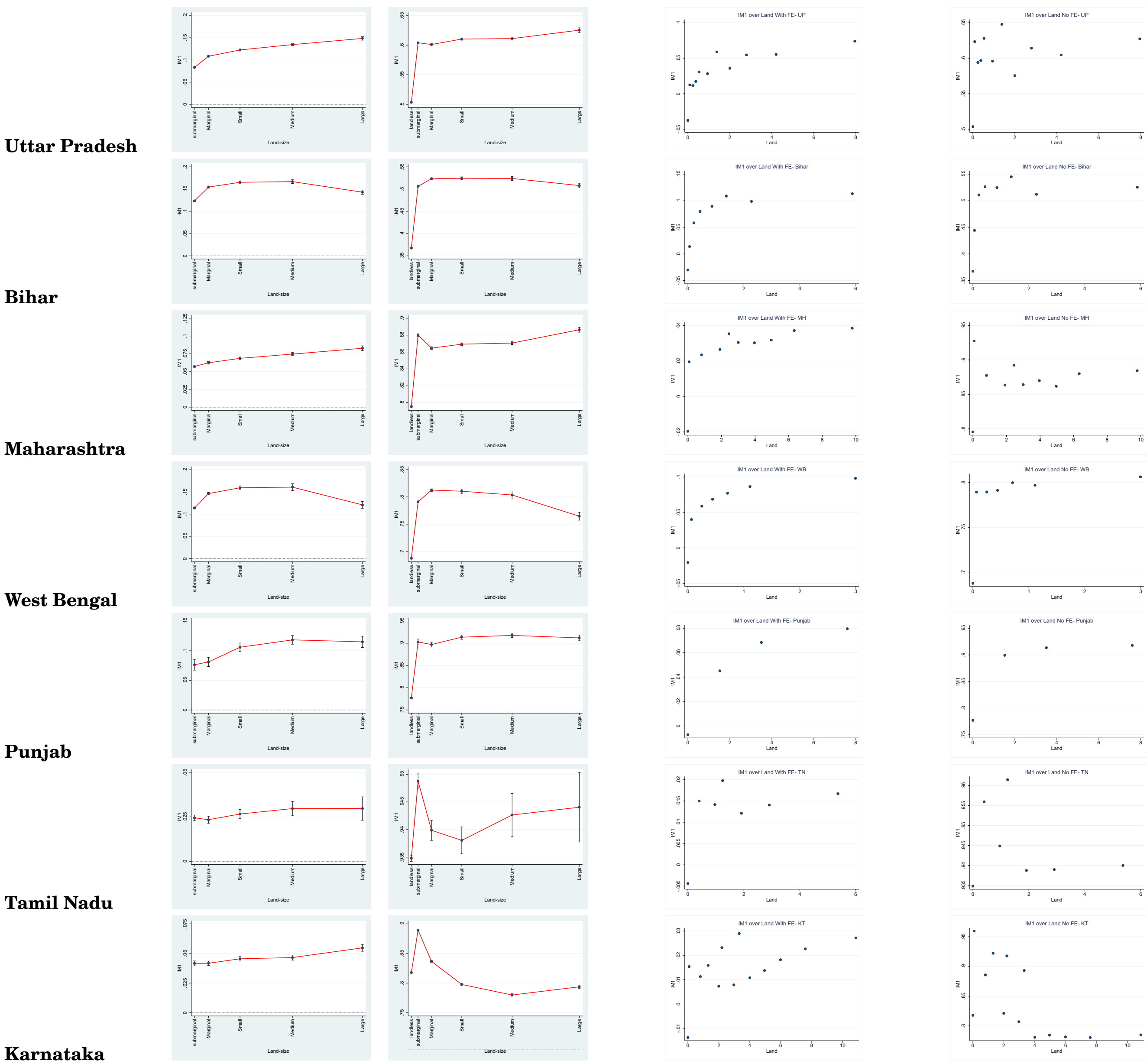


Figure 10: IM^1 over the land distribution by state.

(a) β's from Eq 3 for IM1 **(b) IM1 Raw Means** **(c) IM1 Binscatter with Fixed Effects** **(d) IM1 Raw Binscatter**

Kerala

Rajasthan

Madhya Pradesh

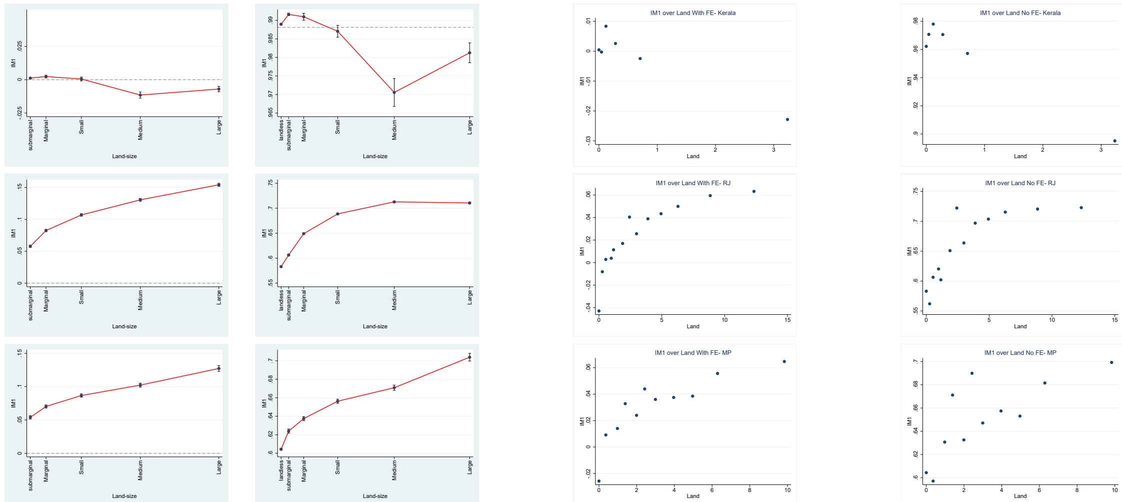


Figure 10: IM^1 over the land distribution by state.

(a) β's from Eq 3 for IM2 (b) IM2 Raw Means (c) IM2 Binscatter with Fixed Effects (d) IM2 Raw Binscatter

Uttar Pradesh

Bihar

Maharashtra

West Bengal

Punjab

Tamil Nadu

Karnataka

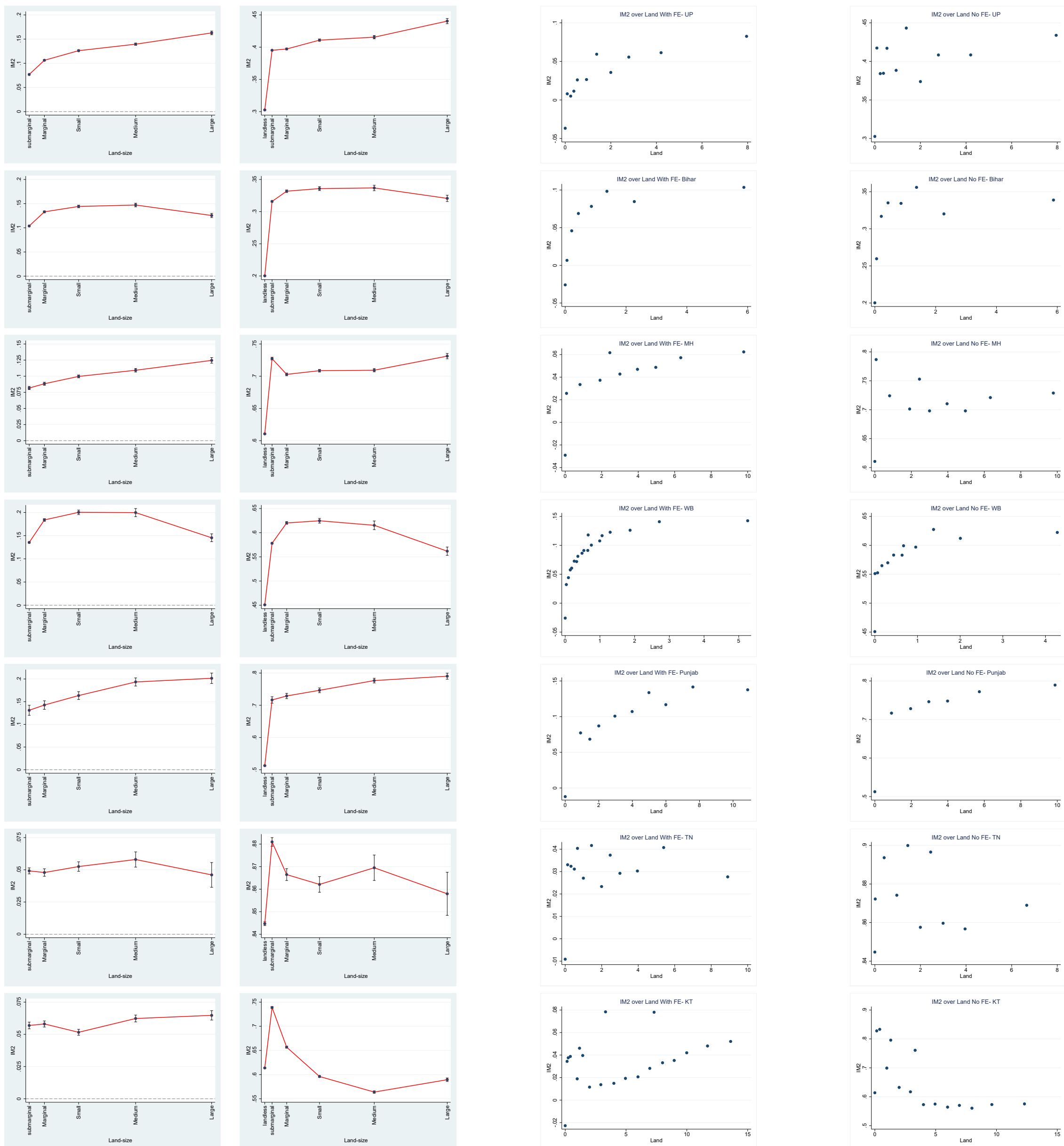


Figure 11: IM^2 over the land distribution by state.

(a) β's from Eq 3 for IM2 **(b) IM2 Raw Means** **(c) IM2 Binscatter with Fixed Effects** **(d) IM2 Raw Binscatter**

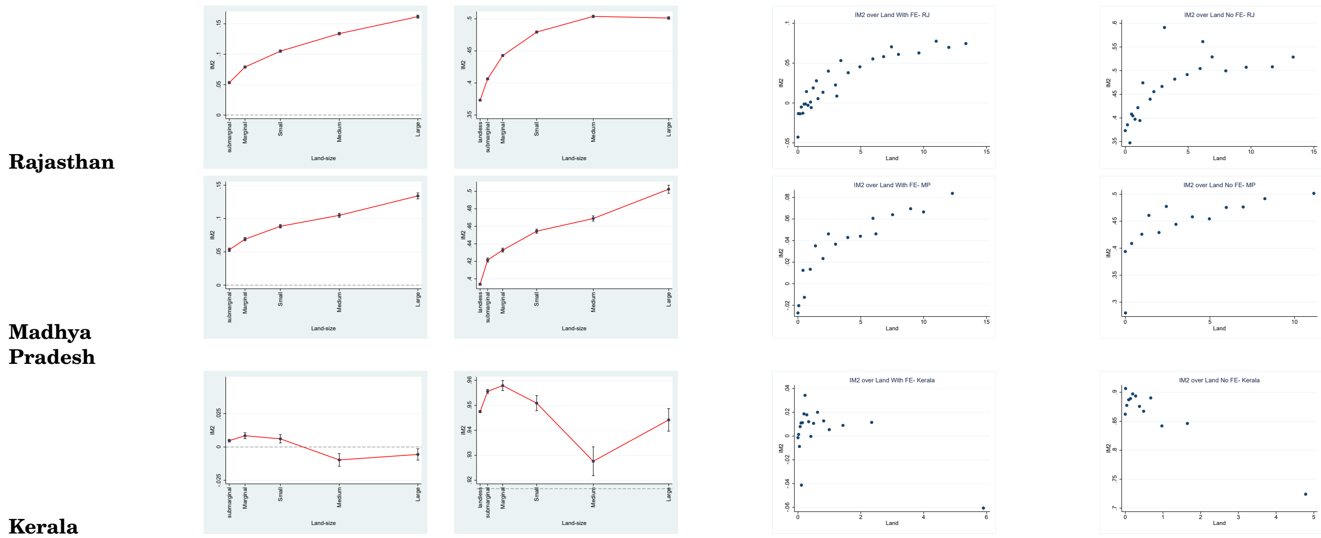


Figure 11: IM^2 over the land distribution by state.

Table 11: Balance around the Konkan–Deccan boundary: RD estimates with control means

Variable	RD estimate	Control mean	Observations
Geography			
Elevation (mean)	−383.148*** (22.083)	775.871	808
Terrain ruggedness (mean)	2.948 (1.517)	19.413	808
Village area (PC11)	−4.331 (114.178)	698.198	808
Population density	0.221* (0.107)	1.521	808
Demography			
Backward caste population share	0.016 (0.011)	0.047	808
Muslim population share	−0.024*** (0.006)	0.501	808
Population share under 20	−0.047* (0.024)	0.299	805
Infrastructure —(per 1,000 people.)			
Primary schools	−0.376 (0.422)	2.906	808
Middle schools	0.418* (0.171)	0.644	808
Secondary schools	0.049 (0.047)	0.098	808
Commercial banks	0.013 (0.009)	0.001	808
Cooperative banks	0.012 (0.009)	0.004	808
Hospitals (all)	0.002 (0.004)	0.013	808
Maternal care centers	0.005 (0.032)	0.046	808
Female/child welfare centers	0.005 (0.032)	0.046	808

Notes: Local linear RD at the Konkan–Deccan boundary with triangular kernel and CCT bandwidths; robust standard errors in parentheses. $^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$. "Control mean (X<0)" is for villages on the Deccan side (negative distance). Units for school, bank, and health variables are per 1,000 population.

Table 12: Within-landless RD checks with covariates

Outcome	**RD estimate**	**Control mean**	**Observations**
Housing quality			
Kutcha dwelling	−0.088 (0.022)	0.655	4790
Pucca dwelling	0.065 (0.022)	0.342	4790
# dwelling rooms	0.063 (0.070)	1.710	4790
Income of highest earning member (monthly)			
Income: < 5k	0.016 (0.017)	0.822	4790
Income: 5–10k	−0.027 (0.015)	0.094	4790
Income: ≥ 10k	0.017 (0.013)	0.073	4790
Assets			
Owns refrigerator	−0.108 (0.013)	0.105	4790
Owns vehicle	0.055 (0.015)	0.878	4790
Owns phone	0.000 (0.006)	0.005	4790
Enterprise & tax			
Pays income/professional tax	0.081 (0.011)	0.041	4790
HH has non-ag enterprise	−0.006 (0.005)	0.010	4790

Notes: Local linear RD (p=1) at cutoff c=0 with triangular kernel; robust standard errors. Outcomes are measured among *landless* households in Raigarh, Pune, Satara, and Ratnagiri; these are *descriptive* comparability checks and not used for identification. Control mean is computed for Deccan-side observations within the optimal bandwidth. "Kutcha" dwellings have non-durable walls/roofs (e.g., thatch, bamboo, plastic); "Pucca" dwellings use durable materials (brick, cement, steel). Income bands refer to monthly rupee earnings of the highest-earning household member. Asset, enterprise ownership, and tax-payment variables are dummies. Each regression controls for family size, caste, age and education of household head, distance to the nearest town, and the presence of banks and hospitals.

Table 13: Sharp RD among the landed

	(1) Landed	(2) Landed	(3) Landed	(4) Marginal	(5) Small	(6) Medium	(7) Large
IM[1] estimate	0.0015	0.0028	0.0040	0.0268	-0.0047	-0.0509	0.0360
(SE)	(0.0155)	(0.0155)	(0.0150)	(0.0213)	(0.0272)	(0.0355)	(0.0580)
N	11086	11086	11025	5164	3341	1928	592
HH controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Village controls	No	No	Yes	Yes	Yes	Yes	Yes

Notes: Sharp RD at the Konkan–Deccan cutoff ($c = 0$), local linear ($p = 1$), triangular kernel; SEs clustered at the household level. Estimates condition on being landed and are therefore post-treatment contrasts; we treat them as descriptive diagnostics rather than causal effects. Columns (4)–(7) split landed households by land size categories (*Marginal*, *Small*, *Medium*, *Large*); see text for definitions. We emply the same set iof controls as in table 4.

Table 14: Debt volumes by land class (USD, per household)

Land class	**Total**	**Total outstanding**	**HH expenditure**
Landless	964.2	902.9	305.7
Submarginal	1,684.1	1,489.7	473.7
Marginal	1,443.7	1,300.7	472.6
Small	1,548.0	1,427.9	474.9
Medium	1,985.1	1,840.7	514.6
Large	3,814.1	3,625.2	681.1

Notes: Total debt refers to all debt accumulated in the calendar year, outstanding debt refers to unpaid debt. HH expenditure refers to debt taken on to meet household expenditure.

Table 15: Marginal–landless mobility gap by banking prevalence (state panels)

	MP	Punjab	UP	MH	RJ	WB	Bihar
Low banking	0.0658***	0.0900***	0.123***	0.0624***	0.0900***	0.161***	0.158***
High banking	0.0739***	0.114***	0.119***	0.0783***	0.114***	0.139***	0.150***
N	388,883	249,983	201,920	138,344	249,983	217,266	285,997
FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Entries are coefficients for the *marginal* land bin relative to the landless, estimated separately in low- vs. high-banking areas (split at the state median of bank-capita). Specifications include village, caste, father- and child-cohort fixed effects. Stars denote p-values: * p<.10, ** p<.05, *** p<.01.

(a) β's from Eq 3 SC's only-IM1 (b) β's from Eq 3-Full Sample-IM1 (c) β's from Eq 3 SC's only-IM2 (d) β's from Eq 3-Full Sample-IM2

Uttar Pradesh

Bihar

Maharashtra

West Bengal

Punjab

Tamil Nadu

Karnataka

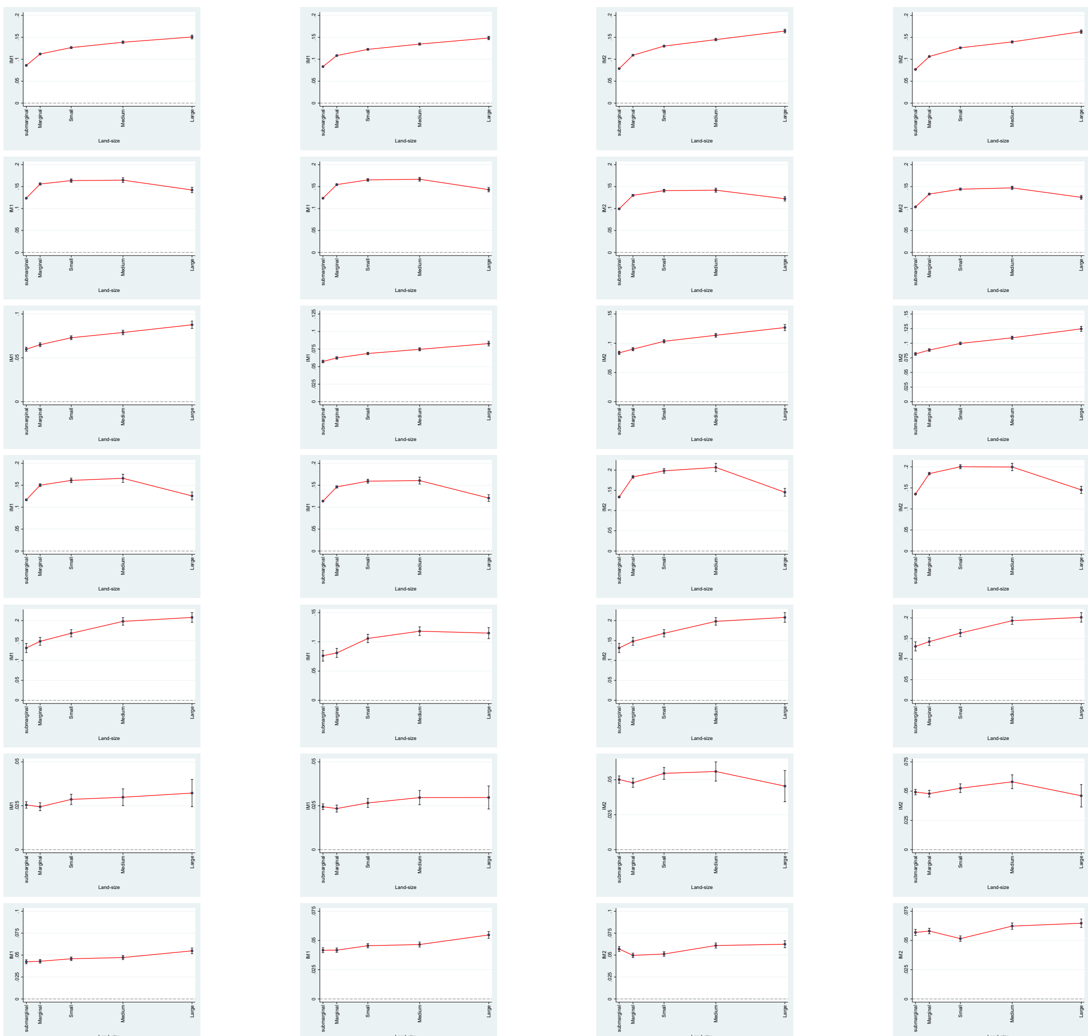
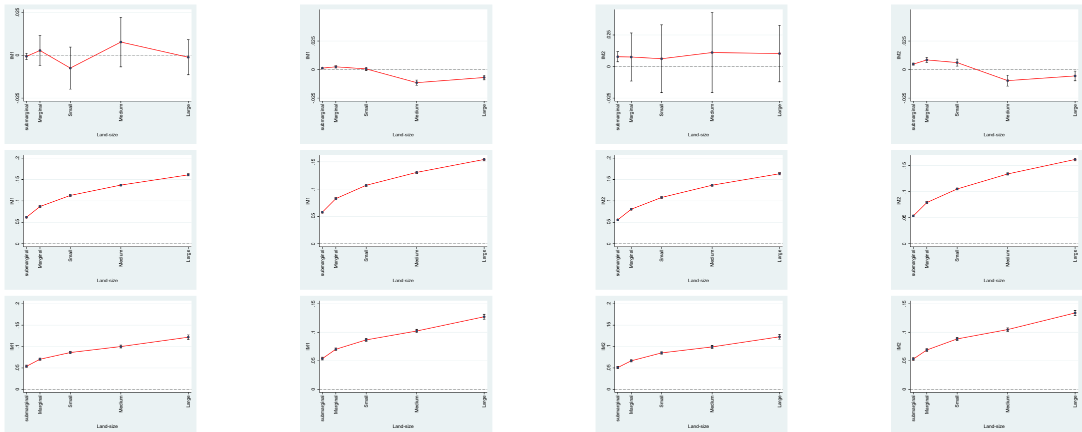


Figure 12: IM gaps over the land distribution by state Backward caste only and full sample.

(a) β's from Eq 3 SC's only-IM1 (b) β's from Eq 3-Full Sample-IM1 (c) β's from Eq 3 SC's only-IM2 (d) β's from Eq 3-Full Sample-IM2



Kerala

Rajasthan

Madhya Pradesh

Figure 12: IM gaps over the land distribution by state Backward caste only and full sample.

B Geo-spatial Appendix

Spatial data construction and variable definitions

Study area and units: We implement the design on villages in Ratnagiri and Raigad (Konkan side) and Pune and Satara (Deccan side). The geographic unit is the 2011 Census village; outcomes are linked to households/father–child pairs within these villages.

GIS sources and preprocessing: We use 2011 Census district and village shapefiles. All spatial operations are done in a projected, metric CRS covering Maharashtra (UTM for the area), so distances are in meters and reported in kilometers. Village geometries are represented by centroids for distance calculations. Administrative geometries are cleaned (snap/tolerance) so shared borders intersect exactly; multi-part and sliver polygons are dissolved before centroiding.

Constructing the Konkan–Deccan boundary. Let $\mathcal{K} = \{\text{Raigad}, \text{Ratnagiri}\}$ and $\mathcal{D} = \{\text{Pune}, \text{Satara}\}$. We extract district boundaries and compute shared border segments via pairwise intersections of boundary polylines:

$$\text{seg}_{kd} = \text{st\_intersection}\big(\text{st\_boundary}(k), \text{st\_boundary}(d)\big), \quad k \in \mathcal{K},\ d \in \mathcal{D}.$$

Segments are combined and dissolved into a single continuous polyline ∂Konkan that serves as the geographic cutoff.

Signed distance (forcing variable) and near-border sample. For each village v, compute the shortest distance from its centroid to the boundary polyline, $\text{dist}(v, \partial\text{Konkan})$ (km). Assign sides by district membership and define the signed running variable

$$X_v \equiv \begin{cases} \text{dist}(v, \partial\text{Konkan}) & \text{if } v \in \mathcal{K}, \\ -\text{dist}(v, \partial\text{Konkan}) & \text{if } v \in \mathcal{D}, \end{cases}$$

so $X_v > 0$ inside Konkan and $X_v < 0$ in the Deccan. The RD sample consists of villages in the four study districts with $|X_v| \leq 20$ km.

Merging outcomes and covariates. Household- and father–child–level outcomes are merged to villages using 2011 Census village identifiers. When outcomes come from microdata, we first attach household records to village IDs (or collapse to village aggregates) before merging to the spatial frame. Geographic covariates (elevation, terrain ruggedness, long-run rainfall, forest cover, distance to nearest town) are constructed at village level from rasters or ancillary GIS layers and joined by village ID.

Variables used in the RD. For a household i in village v:

- Forcing variable: X_v as defined above (signed distance in km).
- Treatment indicator (side of border): $T_{iv} = \mathbf{1}\{X_v \geq 0\}$ for households in Raigad and Ratnagiri; $T_{iv} = 0$ for Pune and Satara.
- Landlessness: $D_{iv} \in \{0, 1\}$ equals 1 if household i is landless and 0 otherwise.
- Outcomes: Y_{iv} denotes the mobility measures at the father–child pair level, defined in the main text.