Credit Enforcement, Misallocation, and Income Disparities across Indian States: A Heterogeneous Agents framework

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Abstract

This paper shows how cross-state differences in credit contract enforcement contribute to income disparities in India. I develop a dynamic heterogeneous-agents model with voluntary and involuntary entrepreneurs, where enforcement shapes borrowing constraints, occupational choices, and factor allocation. A common-credit-market extension allows for capital mobility across states. Stronger enforcement reduces misallocation and raises output; calibrated results suggest it explains about 6 percent of income gaps in 2017–18. Empirically, using NSS data and a judicial reform that accelerated civil case resolution, I find improved enforcement shifts individuals from voluntary entrepreneurship into wage work and involuntary self-employment, consistent with the model's mechanisms.

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1 Introduction

Research over the past several decades has pointed to the importance of financial frictions, broadly, in explaining a significant part of the disparities in per capita incomes across countries. A key challenge remaining from this research is identifying the particular frictions and assessing their quantitative importance. In this paper, I address this challenge by studying the importance of enforcement of credit contracts in driving per capita income differences across Indian states. I develop a quantitative general equilibrium model to study the mechanisms linking enforcement and income disparities and use empirical evidence to validate the model's implications.

In my theoretical analysis, I develop and calibrate a dynamic heterogeneous-agents general equilibrium model with three occupational types — voluntary entrepreneurs, involuntary entrepreneurs, and workers. The model features an endogenous borrowing constraint that depends on the degree of credit contract enforcement and links differences in enforcement to per capita income disparities through the mechanism of factor misallocation. Quantitatively, the model highlights how improved enforcement reallocates resources toward more productive entrepreneurs, raising aggregate output and income. The data on speed of resolution of civil suit cases by state courts is used as a proxy for credit contract enforcement, and is incorporated in the calibration exercise.

To validate the model's implications on occupational reallocation, I complement the theoretical analysis with an empirical exercise exploiting cross-state variation in the implementation of a major judicial reform in 2002—the amendment to the Code of Civil Procedure—that improved judicial speed and, consequently, the enforcement of credit contracts. The empirical strategy follows a difference-in-differences approach to identify the causal impact of improved enforcement on occupational allocation. The results are broadly consistent with the model's predictions.

Studying disparities across Indian states contributes to the macro-development literature for two reasons. First, these disparities are substantial—per capita incomes differ by a factor of seven between the three richest and the three poorest states.[1] Second, examining variation within a single country allows implicit control for several institutional and structural factors that are difficult to hold constant in cross-country analyses - such as laws, legal origins, national policies, and other country-wide characteristics. This within-country framework is advantageous not only for empirical identification but also for the quantitative calibration of the theoretical model, as it enables a consistent comparison of state-level outcomes under a common macroeconomic and institutional environment while allowing enforcement of credit contracts to vary across states.

A key feature of both the theoretical model and the empirical analysis is the distinction between

[1] In 2017–18, the average per capita GDP of the top three richest states (Goa, Sikkim, and Delhi) was nearly seven times that of the bottom three (Bihar, Uttar Pradesh, and Manipur).

voluntary and involuntary entrepreneurs. This distinction is motivated by the fact that India has a large number of very small firms—classified here as involuntary firms—accounting for roughly 30 percent of the working population and typically owned by individuals who are self-employed because they cannot find wage employment. There is clear evidence in the literature that enforcement of credit contracts affects access to credit and the performance of both voluntary and involuntary firms in India (Lilienfeld-Toal et al., 2012a; Chemin, 2012).[2]

The theoretical model evaluates the impact of credit contract enforcement on per capita GDP and other macroeconomic outcomes by aggregating its effects on individual-level decisions and incomes. State-level enforcement capacity determines individual's ability to rent capital, the scale of firms they can operate, and the profits they can earn as firm owners. The effects of enforcement are heterogeneous across individuals, depending on their asset holdings, entrepreneurial ability, and labor market opportunities. Occupational choice lies at the core of the model's mechanism: in a general-equilibrium setting where wages and interest rates adjust endogenously, variation in credit enforcement alters the relative returns to different occupations, inducing a reallocation of individuals across them and, in turn, shaping aggregate productivity and income.

Involuntary entrepreneurs are introduced in the model through labor-market frictions that govern an individual's probability of finding a wage job. Individuals who wish to work but cannot secure employment operate small, subsistence-level firms out of necessity rather than choice. These firms can be credit-dependent, as even subsistence operations require some minimum level of working capital. The large share of credit-dependent involuntary entrepreneurs in the workforce therefore reinforces the link between credit contract enforcement and aggregate productivity differences across states.

Each period, individuals are heterogeneous in entrepreneurial productivity, asset holdings, and labor-market opportunity. They make three key decisions: (i) optimal choice of capital and labor if they have to operate a firm, (ii) the occupational choice, and (iii) the consumption–savings decision. Asset accumulation is determined endogenously through the forward-looking savings problem. Individuals with a labor opportunity compare the potential incomes from wage work (a fixed wage) and from firm ownership (constrained optimal profits) to choose their occupation. Those without a labor opportunity have no option but to establish a firm. If profits from firm ownership are below the prevailing wage, they are classified as involuntary entrepreneurs; otherwise, they are voluntary entrepreneurs.

Stronger enforcement of credit contracts raises both wages and interest rates by increasing

[2]Lilienfeld-Toal et al. (2012a) find that improved enforcement of credit contracts increases the borrowings and profits of voluntary firms on average, while Chemin (2012) finds that faster judicial processes enhance credit access and investment for involuntary firms.

the aggregate demand for labor and capital. Its effect on access to finance is heterogeneous across individuals, depending on which force dominates—the relaxation of borrowing constraints or the rise in input costs. For talented but asset-poor individuals, the easing of borrowing constraints dominates, expanding their access to credit and enabling them to operate at a larger scale. For low-skill individuals with low desired capital, however, the increase in borrowing costs and wages dominates, effectively tightening their access to finance. These distributional differences in credit access and production costs alter relative potential incomes across occupations, leading to a reallocation of individuals in equilibrium: the share of voluntary entrepreneurs declines, while the shares of involuntary entrepreneurs and workers increase. Overall, the more talented individuals are now in the voluntary entrepreneurship category, operating larger and more productive firms. This selective reallocation reduces misallocation of talent, capital, and labor across production units, thereby improving aggregate efficiency and raising per capita output.

I extend the benchmark model to allow for national integration in financial markets, where states share a common interest rate determined by aggregate capital supply and demand. This extension highlights how capital mobility can amplify institutional differences: states with stronger enforcement attract savings, expand firm scale, and accumulate more capital, while weaker-enforcement states experience capital outflows and constrained investment.

The calibration exercise proceeds by first estimating national parameters common to all states and then calibrating the state-specific degree of credit contract enforcement, ϕ_s using two complementary approaches: (i) where ϕ_s is directly inferred from state-level civil case disposal speeds, and (ii) where ϕ_s is chosen such that the model-generated external finance-to-GDP ratio matches observed values in the RBI Handbook of Statistics on Indian States (2017–18). For each specification, the model is solved separately for every state to generate implied values for GDP per capita and average voluntary firm size. Under Approach 1, a regression of data GDP per capita on model-predicted GDP per capita yields an R-squared of 0.06,indicating that cross-state differences in enforcement alone explain about 6 percent of income disparities in 2017–18. Approach 2 suggests that variation in credit-market access linked to enforcement accounts for 3.5 percent of the cross-state variation in per-capita income. In both cases, the model reproduces broad differences in average voluntary firm size observed across states.

In the empirical exercise – using multinomial logit regressions, I estimate the causal impact of change in judicial speed–on individuals' occupational choices across Indian states. The empirical identification relies on a difference-in-differences (DiD) design following Chemin (2012), which exploits cross-state variation in the implementation intensity of the 2002 Civil Procedure Code (CPC) Amendment Act in India. The CPC governs the procedures of civil courts, and the 2002 reform introduced multiple measures to expedite judicial processes, including mandatory time limits at various stages of litigation, restrictions on the right to appeal, empowerment of courts to refer disputes to alternative dispute resolution mechanisms, and reduced adjournments. Since individual states possess legislative authority to amend the CPC, several had already enacted similar procedural amendments before 2002, thereby receiving different "policy doses" when the national reform was implemented. This heterogeneity in pre-reform adoption generates the variation exploited for identification.

I use individual-level data from three rounds of the *National Sample Survey Employment and Unemployment Surveys*—the 50$^{\text{th}}$ (1993–94), 55$^{\text{th}}$ (1999–2000), and 61$^{\text{st}}$ (2004–05) rounds—which together represent pre- and post-reform periods around the 2002 Civil Procedure Code Amendment Act (two pre-periods and one post period). Occupations are classified into three mutually exclusive categories: voluntary entrepreneurs (employers hiring labor), involuntary entrepreneurs (own-account workers without hired labor), and workers (wage employees). The regression results indicate a statistically siignicant decline in voluntary entrepreneurship and a rise in involuntary entrepreneurship and workers in states that experienced larger gains in judicial efficiency. Placebo interactions using the 1994 pre period show no significant differential shifts by treatment intensity, supporting the parallel-trends assumption. Education enters with the expected composition effects: higher schooling raises the probability of voluntary entrepreneurship, lowers the probability of involuntary entrepreneurship, and raises the probability of wage work. These findings reinforce the model's central mechanism: improvements in credit contract enforcement, proxied by faster judicial systems, reshape occupational allocation through general-equilibrium effects on wages and entry thresholds for entrepreneurship.

This paper contributes to two strands of literature. First, it advances quantitative macro-development research linking contract enforcement to resource misallocation and aggregate productivity in developing economies. Second, it adds to the empirical literature on how credit contract enforcement influences access to finance, firm expansion, and individual's occupational choices.

A central insight in the quantitative macro-development literature is that weak enforcement of credit contracts distorts access to external finance and generates large aggregate productivity losses. A foundational contribution is Buera et al. (2011), who embed imperfect credit enforcement in a general equilibrium model with heterogeneous entrepreneurs and show that borrowing constraints lead to severe capital misallocation and persistent income gaps. Relatedly, Antunes et al. (2008) show that improvements in enforceability expand entrepreneurial activity and raise aggregate output, while Buera and Shin (2013) demonstrate that weak enforcement can generate history-dependent misallocation, with long-lasting effects on productivity even after institutional reforms. Together, these studies highlight contract enforcement as a first-order institutional friction shaping aggregate outcomes through occupational choice, firm scale, and capital allocation.

An important feature of my model is the incorporation of involuntary, or "necessity," entrepreneurs, who operate small firms not due to exceptional talent but due to limited employment opportunities. In Buera et al. (2020), such entrepreneurs arise when individuals receive a low labor-productivity draw that makes wage employment unattractive. In contrast, in my model a poor labor-market opportunity draw precludes wage employment altogether, compelling individuals to operate as constrained entrepreneurs in that period. This formulation reflects the labor-surplus conditions in developing economies such as India, where a substantial share of self-employment is driven by lack of formal job opportunities rather than entrepreneurial comparative advantage. By making necessity entrepreneurship a binding constraint rather than a discretionary response, my model generates a larger and more persistent pool of small-scale, low-productivity firms. As a result, limited credit contract enforcement not only restricts the scale of high-productivity entrepreneurs—as in standard enforcement models—but also amplifies misallocation by trapping necessity entrepreneurs in chronically undercapitalized occupations, thereby magnifying aggregate TFP and income losses.

Empirically, a large literature documents that legal enforcement plays a key role in shaping financial access and firm outcomes. Cross-country evidence shows that weaker investor protection and judicial enforcement are associated with shallower financial markets (La Porta et al., 1997; Gropp et al., 1997). Within India, Lilienfeld-Toal et al. (2012b) show that the introduction of Debt Recovery Tribunals increased borrowing and investment but raised equilibrium interest rates, with heterogeneous effects across firms. Chemin (2012) demonstrate that the 2002 Civil Procedure Code reform improved credit access and investment among informal enterprises, while Ponticelli and Alencar (2014) and Rajan and Ramcharan (2020) further document how judicial efficiency affects credit reallocation and firm dynamics.

While prior empirical work has examined how financial frictions influence occupational sorting, the role of credit contract enforcement in shaping occupational choice has not been studied in a micro-founded setting. Levine and Rubinstein (2018) estimate a multinomial logit model of occupational choice, showing that human capital and liquidity constraints jointly determine selection into entrepreneurship and wage work. I build on this structure but combine it with a difference-in-differences strategy exploiting cross-state variation in judicial efficiency induced by the 2002 Civil Procedure Code Amendment Act. This approach enables me to micro-found and estimate how improvements in credit enforcement translate into changes in the occupational composition—specifically, the shares of voluntary entrepreneurs, involuntary entrepreneurs, and wage workers—across Indian states.

The remainder of the paper is organized as follows: Section 2 describes the model and its mechanisms. Section 3 describes the calibration strategy and results. Section 4 describes the empirical analysis on the impact of improvement in judicial speed on occupational choices of the working population in India. Section 5 concludes.

2 The Model

This section develops a dynamic general equilibrium model with heterogeneous agents in which credit enforcement frictions distort occupational choices and firm scale, leading to measurable effects on TFP and per capita output. The model features three key elements: (1) agents who choose between voluntary entrepreneurship, involuntary entrepreneurship, and wage employment based on heterogeneous productivity draws; (2) endogenous borrowing constraints tied to state-specific enforcement efficiency (ϕ); and (3) labor market frictions (χ) that generate involuntary firms. Each state is modeled as a closed economy, with its own labor and capital markets, allowing us to capture cross-state variation in institutional quality and its aggregate implications.

The economy is populated by a continuum of infinitely lived individuals of measure N. In each period, individuals consume, save, and earn income either by operating a firm or by supplying labor to other firms. Production takes place in firms operated by entrepreneurs, who may be classified as voluntary or involuntary. All firms produce a homogeneous good, which is consumed by individuals and whose price is normalized to one. Entrepreneurs demand capital and labor to operate their firms, while workers supply labor. Individual asset holdings collectively constitute the supply of capital, which is rented to firms through a competitive capital market. The economy features three markets—goods, labor, and capital—which clear competitively each period. The economy is geographically segmented into states. In the baseline model, each state is modeled as a closed economy: labor and capital markets clear within states, and individuals participate only in the markets of their own state.

Every period, individuals receive a draw of a two-dimensional vector $\mathbf{z} = \{z, \ell\}$, where z represents entrepreneurial productivity, $\ell \in \{0, 1\}$ indicates access to wage employment. log(z) follows an AR(1) process with persistence ρ and variance of error term σ. The labor opportunity shock ℓ captures frictions in the wage labor market: with probability χ, $\ell = 1$ and the individual can find a wage job; with probability $1-\chi$, $\ell = 0$ and the individual cannot find wage work. Individuals choose savings and occupational status each period to maximize the expected discounted sum of utility over an infinite horizon. Individuals who choose to operate firms each period rent capital and hire labor optimally, subject to credit enforcement frictions. In addition to households and firms, the economy features competitive financial intermediaries—such as banks—that accept deposits from households and rent capital to firm owners.

Subsections 2.1 and 2.2 describe the model's structure in detail, while Subsection 2.3 discusses the core mechanisms that drive the model's results. Subsection 2.4 discusses the model extension with common capital market across states

2.1 Individual's Optimization Problem

2.1.1 Preferences, Technology, and Credit Enforcement

The economy is populated by infinitely lived individuals who choose consumption sequences $\{c_t\}_{t=0}^{\infty}$ to maximize expected lifetime utility,

$$U = \mathbb{E}\sum_{t=0}^{\infty}\beta^t u(c_t), \tag{1}$$

where period utility is given by

$$u(c_t) = \frac{c_t^{1-\gamma}-1}{1-\gamma}. \tag{2}$$

Here, $\beta \in (0,1)$ is the discount factor and γ denotes the coefficient of relative risk aversion.

Each period, individuals choose an occupation that determines their income. A labor-market opportunity shock $\ell \in \{0,1\}$ governs access to wage employment. When $\ell = 1$, individuals may choose between wage work and firm operation; when $\ell = 0$, wage employment is unavailable and individuals must operate a firm. All workers supply one unit of labor and earn a common wage w.

Individuals who operate firms demand capital k and labor l to produce output according to

$$f(k,l,z) = zk^{\alpha}l^{\theta}, \tag{3}$$

where z denotes entrepreneurial productivity and $\alpha + \theta < 1$ implies decreasing returns to scale. Firm profits are given by

$$\pi(k,l;R,w,z) = zk^{\alpha}l^{\theta} - Rk - wl, \tag{4}$$

where R is the rental rate of capital. Entrepreneurs are classified as *voluntary* if profits exceed the wage w, and as *involuntary* otherwise.

Capital is intermediated by competitive financial institutions that collect deposits from individuals at interest rate r and rent capital to firms at rate R. Intermediaries earn zero profits, implying

$$R = r + \delta, \tag{5}$$

where δ is the depreciation rate of capital. Individuals cannot hold negative assets, so $a \geq 0$.

Credit contracts are imperfectly enforced. The parameter $\phi \in [0, 1]$ captures the degree of contract enforcement, with higher values indicating stronger enforcement. When enforcement is imperfect ($\phi < 1$), entrepreneurs may renege on their credit obligations and retain a fraction $(1-\phi)$ of revenues net of labor payments and undepreciated capital, forfeiting their collateral assets a. To deter default, financial intermediaries impose a borrowing limit $\bar{k}(a, z, \phi)$ that satisfies the incentive compatibility constraint

$$\max_{l}\{zk^{\alpha}l^{\theta} - wl\} - Rk + a(1+r) \geq (1-\phi)\left[\max_{l}\{zk^{\alpha}l^{\theta} - wl\} + (1-\delta)k\right]. \tag{6}$$

This constraint implies that the maximum capital rented to a firm is increasing in collateral assets a, entrepreneurial productivity z, and enforcement quality ϕ.

2.1.2 Individual Optimization Problem

Individuals choose consumption, savings, and occupation to maximize lifetime utility as defined in equation (2). At the beginning of each period, an individual observes the state (a, z, ℓ), where a denotes asset holdings, z entrepreneurial productivity, and $\ell \in \{0, 1\}$ indicates access to wage employment. Individuals then choose next period's assets a' and an occupation.

Let $v(a, z, \ell)$ denote the value function. When $\ell = 1$, individuals can choose between wage work and firm operation; when $\ell = 0$, wage employment is unavailable and individuals must operate a firm. The value function is therefore

$$v(a, z, \ell) = \max\{v^W(a, z, \ell), v^F(a, z, \ell)\}\mathbf{1}\{\ell = 1\} + v^F(a, z, \ell)\mathbf{1}\{\ell = 0\}. \tag{7}$$

The value of wage work satisfies

$$v^W(a, z, \ell) = \max_{c, a' \geq 0}\left\{u(c) + \beta\mathbb{E}_{z',\ell'}[v(a', z', \ell')]\right\} \tag{8}$$

subject to

$$c + a' \leq w + (1+r)a. \tag{9}$$

The value of firm operation satisfies

$$v^F(a,z,\ell) = \max_{c,a',k,l\geq 0} \left\{u(c) + \beta \mathbb{E}_{z',\ell'}[v(a',z',\ell')]\right\} \tag{10}$$

subject to

$$c + a' \leq zk^{\alpha}l^{\theta} - Rk - wl + (1+r)a, \tag{11}$$

and the enforcement-induced borrowing constraint

$$k \leq \bar{k}(a,z,\phi). \tag{12}$$

Occupational choice is static conditional on prices. When $\ell = 1$, individuals choose firm operation if contemporaneous profits exceed the wage w and wage work otherwise; such firm operators are referred to as *voluntary entrepreneurs*. When $\ell = 0$, individuals must operate a firm; if profits fall below w, they are classified as *involuntary entrepreneurs*. Firm owners rent capital and hire labor each period to maximize static profits.

Let (k^u, l^u) denote unconstrained profit-maximizing inputs and (k^o, l^o) denote optimal inputs under imperfect enforcement. The borrowing constraint implies

$$k^o = \min\{k^u, \bar{k}(a,z,\phi)\}, \tag{13}$$

with l^o chosen optimally given k^o.

2.2 Stationary Competitive Equilibrium

A stationary competitive equilibrium consists of an invariant distribution $G(a,z,\ell)$ over individual states, policy functions $\{a'(a,z,\ell), o(a,z,\ell), k(a,z,\ell), l(a,z,\ell)\}$, borrowing limits $\bar{k}(a,z,\phi)$, and prices (w,R,r) such that:

1. Given prices (w,R,r) and borrowing limits $\bar{k}(a,z,\phi)$, individual policy functions solve the optimization problem defined in equations (8)–(13).

2. The capital market clears:

$$\int k(a,z,\ell)\, dG(a,z,\ell) = \int a\, dG(a,z,\ell). \tag{14}$$

3. The labor market clears:

$$\int l(a,z,\ell)\,dG(a,z,\ell) = \int \mathbf{1}\{o(a,z,\ell) = W\}\,dG(a,z,\ell). \tag{15}$$

2.3 Model Mechanisms

This section presents the model mechanisms that link the degree of credit contract enforcement to occupational choices, the scale of firms, resource allocation, and aggregate outcomes. The key parameter of interest is ϕ, which governs the enforcement of credit contracts and, consequently, which impacts the extent to which firm owners can borrow against collateral. A higher ϕ relaxes borrowing constraints, allowing more productive but asset-poor individuals to access capital, operate larger firms, and earn higher profits.

These micro-level effects induce reallocation across occupations. In partial equilibrium, individuals who would otherwise be involuntary entrepreneurs or workers may now enter voluntary entrepreneurship. At the same time, firms expand in scale, leading to more efficient use of entrepreneurial talent and capital. In general equilibrium, the increased demand for capital and labor raises the interest rate and the wage, which further shapes individual incentives and the occupational distribution.

Together, these forces shift production toward larger, more productive firms and reallocate capital and labor toward individuals with higher entrepreneurial ability, ultimately raising aggregate output per capita. The rest of the section traces these effects in detail, focusing solely on the implications of ϕ while holding all other model parameters constant.

To do so, it is important to first outline how the general equilibrium of the model is determined. The general equilibrium solution of the model requires jointly solving for the equilibrium prices of labor and capital— w and r—as well as the individual-level policy functions: capital demand k, labor demand l, occupational choice o, and asset accumulation a'. The key model outcomes—such as income per capita, capital per capita, occupational shares, and firm size distributions—are derived by aggregating these policy functions over the stationary joint distribution of individual states at the equilibrium prices.

To understand how changes in credit enforcement ϕ affect these outcomes, we must examine how ϕ influences both the policy functions and the general equilibrium prices r and w. I proceed in two steps. First, I analyze the partial equilibrium effects of ϕ—how enforcement affects individual decisions when prices are held fixed. Then, I turn to the general equilibrium effects, showing how these individual responses influence aggregate factor demands, thereby altering equilibrium prices, which in turn feed back into occupational choices, resource allocation, and aggregate output.

2.3.1 Partial Equilibrium effects of ϕ

We begin by analyzing the effects of contract enforcement ϕ in partial equilibrium, holding general equilibrium prices r and w fixed. This isolates the direct impact of ϕ on agents' decisions without incorporating feedback from aggregate factor markets.

The key mechanisms operate through the individual policy functions. Recall that individuals differ in their asset level a, entrepreneurial productivity z, and labor opportunity ℓ. Given these state variables and fixed prices, individuals first evaluate their optimal choices of capital and labor, if they had to set up a firm. Then, comparing their incomes in the current period between the possible choices of occupation they have, choosing the one that gives them maximum income, they are either a voluntary entrepreneur, involuntary entrepreneur, or a worker. All individuals choose how much to save for the next period.These decisions are encoded in the policy functions k(a,z,ℓ), l(a,z,ℓ), o(a,z,ℓ), and a'(a,z,ℓ).

(a) **Individual Policy Functions at Fixed Prices**

i. Capital Demand $k(a, z, \ell)$ and Labor Demand l(a,z,ℓ):

We begin by examining the policy functions for capital and labor demand $k(a, z, \ell)$ and l(a,z,ℓ). When $\ell = 1$ the individual has the option to become either a firm owner or a worker. For a given pair (a,z), if the potential profits by being a firm owner are less than w, the individual chooses to work, and both capital and labor demands are zero, (i.e., k = 0 and l = 0). If instead the firm ownership yields higher returns, the individual optimally chooses k and l for his firm, subject to the collateral constraint.

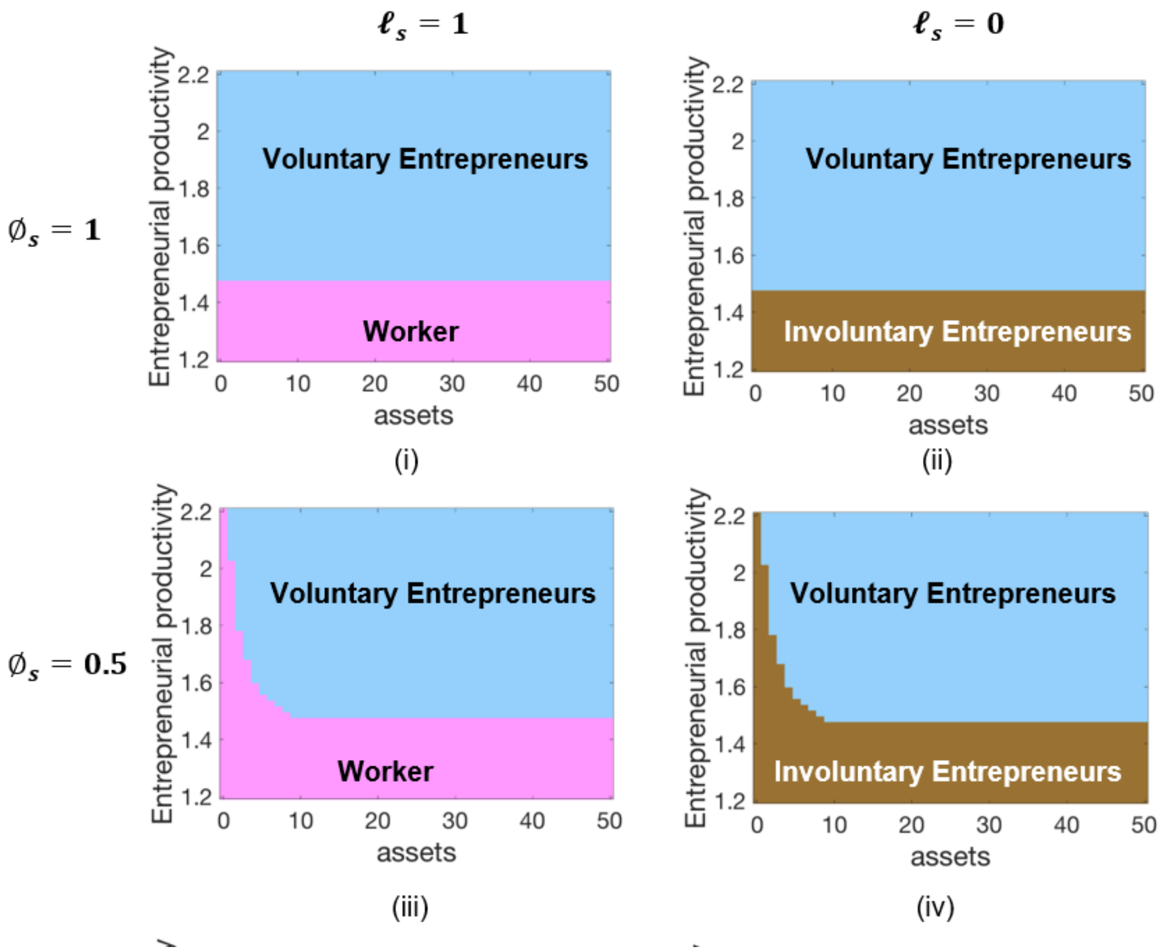
If $\ell = 0$, the individual cannot be a worker and must set up a firm. In this case, capital and labor demands are always chosen optimally, given the borrowing constraint.

For every combination of a, z, and ℓ; k and l are increasing in ϕ, as $\bar{k}$ is increasing in ϕ.

ii. Occupational Choice $o(a, z, \ell)$:

Figure 1 presents the occupational choice policy functions under four combinations of ϕ's and ℓ's respectively: (i) $\ell = 1$, $\phi = 1$, (ii) $\ell = 0$, $\phi = 1$, (iii) $\ell = 1$, $\phi = 0.5$, (iv) $\ell = 0$, $\phi = 0.5$, for a given fixed set of w and r. In each panel, occupational choice is represented as a function of the individual state variables: assets a (x-axis), productivity z (y-axis), and labor opportunity ℓ (column grouping). The shaded regions indicate the occupation type: pink for workers, blue for

Figure 1: Occupational Choice Policy Functions - Partial Equilibrium



voluntary entrepreneurs, and brown for involuntary entrepreneurs. When $\ell = 1$ individuals choose to be workers if the profits from voluntary entrepreneurship are less than the wage w; otherwise, they choose to be firm owners. When $\ell = 0$, they have no option but to become firm owners. In this case if profits are greater than w they are voluntary entrepreneurs, otherwise they are involuntary entrepreneurs. Cases (i) and (ii) (and similarly (iii) and (iv)) share the same cut-off in (a,z) space for entry into voluntary entrepreneurship, since involuntary entrepreneurs are precisely those who would have chosen to be workers had they access to the labor market.

Diagrams (i) and (ii) in figure 1 represent the case of perfect enforcement of credit contracts (i.e., $\phi = 1$), where the borrowing constraint is fully relaxed and capital rental is unconstrained. Consequently, firm owners rent the unconstrained optimal quantities of capital and labor—denoted by k^u and l^u respectively — as determined in equation (14). Since the collateral constraint does not bind, the resulting profits from firm ownership are independent of the individual's asset level a.

Given fixed w and r, when $\phi = 1$, occupational choice depends only on entrepreneurial productivity z. In both cases—$\ell = 0$ (no labor market access) and $\ell = 1$ (labor market access)—the condition $z(k^u)^\alpha(l^u)^\theta - Rk^u - wl^u > w$ defines the cutoff value of z that separates voluntary entrepreneurs from workers (when $\ell = 1$) or from involuntary entrepreneurs (when $\ell = 0$).

In cases (iii)–(iv), where there is imperfect enforcement of credit contracts, profits from firm ownership are determined by renting constrained optimal levels of capital and labor, as described in equations (15)–(16). In these scenarios, the profit function and hence the occupational choice depend jointly on an individual's asset level a and productivity z. When assets are sufficiently high, the collateral constraint derived from condition (7) does not bind, allowing the entrepreneur to rent the unconstrained optimal levels of capital and labor. In such cases, profits are independent of a and depend solely on z, leading to a productivity-based cutoff for selecting into voluntary entrepreneurship—analogous to cases (i) and (ii). In contrast, when assets are low and the constraint binds, the entrepreneur's ability to operate a voluntary firm is limited by available collateral, making both a and z jointly relevant for determining whether firm profits exceed the wage w. As asset holdings decline, a higher level of productivity z is required to compensate for the tighter constraint. Moreover, a lower enforcement parameter ϕ exacerbates this effect by tightening the borrowing limit further, thus raising the productivity threshold needed for low-asset individuals to become voluntary entrepreneurs.

iii. Asset Choice $a'(a, z, \ell)$:

Holding wages w and and interest rates r, an increase in the enforcement parameter ϕ, relaxes the borrowing constraint. As a result, firm owners are able to rent more capital k and hire more labor l. This expansion in firm scale raises profits and incomes for all existing firm owners and also induces some individuals to switch from wage employment to firm ownership in partial equilibrium.

Higher incomes translate into higher savings, so the next-period asset level a' tends to rise when ϕ increases. However, when enforcement is weak (ϕ is low), individuals with low assets but high productivity z face tight collateral constraints and have a strong incentive to self-finance. For these individuals, a lower ϕ raises the marginal value of savings because accumulating collateral is a precondition for scaling up production in the future. This effect pushes a' upward when ϕ decreases.

Thus, the net effect of a change in c on an individual's savings decision depends on the balance between:

The income effect: Higher ϕ increases profits and raises savings mechanically.

The precautionary/self-financing effect: Lower ϕ increases the shadow value of collateral and induces higher saving among constrained but productive agents.

Which force dominates will depend on the agent's current asset level, productivity draw, and how close they are to the collateral constraint.

2.3.2 Impact of ϕ on general equilibrium r and w

At the stationary equilibrium, the interest rate r and wage w jointly clear the capital and labor markets. Given r and w, aggregate demand for capital and labor is the sum of all firm owners input demands of capital and labor respectively, while aggregate supply of capital equals total asset holdings, and aggregate supply of labor equals the mass of individuals choosing to work.

At a given r and w, an increase in ϕ increases aggregate demand for both capital and labor - as relaxed borrowing constraints allow entrepreneurs to rent more capital, operate at a larger scale, and induce some workers to switch to entrepreneurship. At a given r and w, an increase in ϕ may increase/decrease aggregate supply of capital based on which effect between -income/precautionary/self-financing effect is stronger in aggregate, whereas aggregate supply of labor decreases as fewer individuals choose wage work. Since the increase in aggregate demand dominates the change in supply, both r and w rise as ϕ rises in general equilibrium.

2.3.3 Impact of ϕ on general equilibrium outcomes

Figure 2 presents the occupational choice policy functions in the general equilibrium case, with the regions for constrained and unconstrained voluntary and involuntary entrepreneurs demarcated. Panels (i) and (ii) depict individual occupational choices for $\ell = 1$ and $\ell = 0$, respectively, under the case where the economy-wide enforcement parameter $\phi = 1$. Panels (iii) and (iv) present the corresponding choices when $\phi = 0.5$.

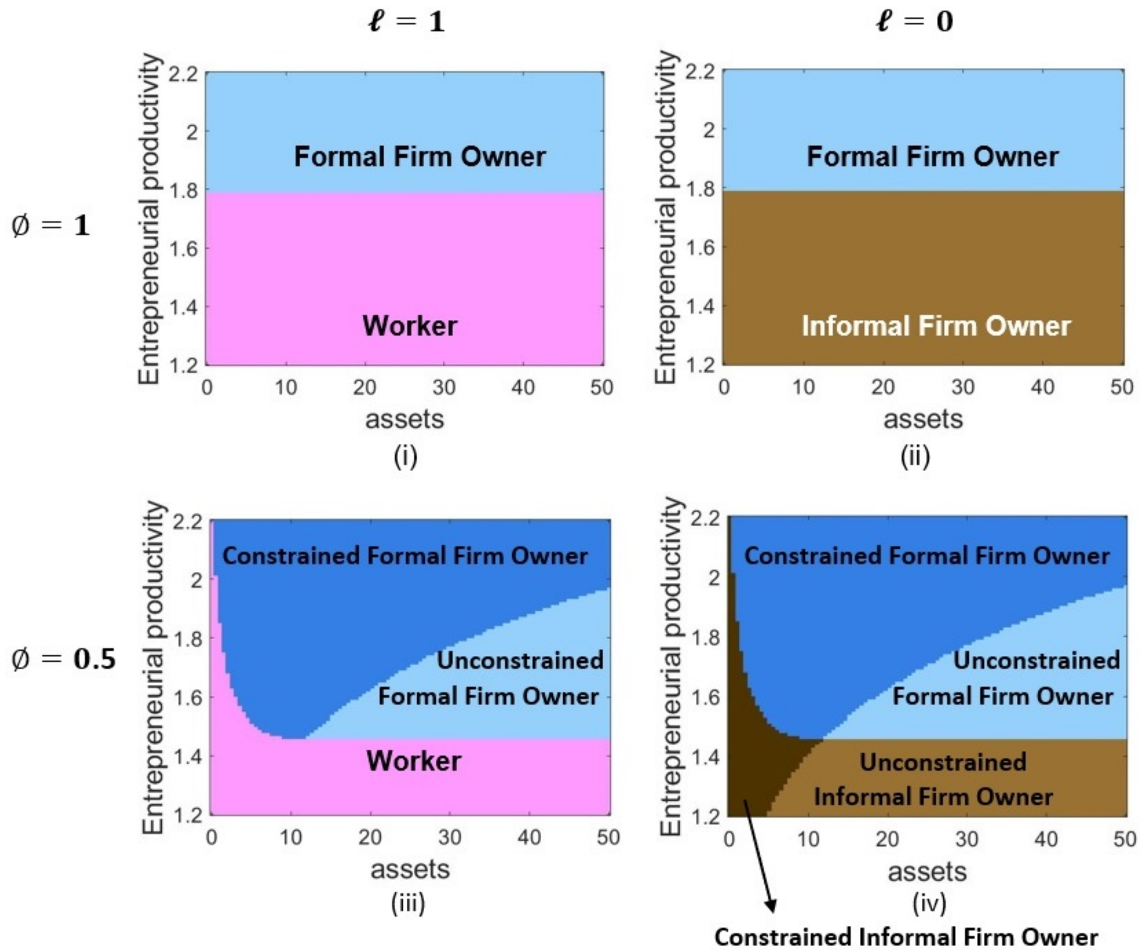
The key difference relative to Figure 1 is that, as ϕ increases, the equilibrium wage w rises, which increases the productivity cutoff z for entry into voluntary entrepreneurship. Under perfect enforcement (panels (i) and (ii)), no firm owners face borrowing constraints. Under imperfect enforcement (panels (iii) and (iv)), individuals with lower asset holdings are more likely to be capital constrained.

Table 1 presents the model-generated simulations for different ϕ's. With increasing ϕ, both r and w rise, as discussed above. However, the impact of increasing ϕ on access to credit is heterogeneous across individuals. A higher ϕ relaxes the borrowing constraint, allowing individuals to rent more capital, but it also raises r, which makes borrowing more expensive. These two effects work in opposite directions.

The net effect depends on the individual's type:

High-ability individuals with low assets benefit the most. For them, the loosening of the

Figure 2: Occupational Choice Policy Functions - General Equilibrium



borrowing constraint dominates the rise in r, enabling them to access more credit and expand firm size. Low-ability individuals may actually be worse off. Because their unconstrained optimal demand for capital is already low, the rise in r may have a stronger effect relative to the loosening of the constraint. As a result, their effective access to credit may decline as ϕ increases.

Overall, with improved borrowing ability and a higher wage rate, individuals reallocate across occupations in the economy. Only those individuals who can generate profits exceeding the higher wage (and who can still cover the increased interest and wage costs) choose to operate as voluntary firms. The average ability, profit levels, scale of operations, and output of voluntary entrepreneurs are substantially higher compared to when ϕ was lower.

The share of voluntary entrepreneurs may decline as ϕ increases. Higher wages raise the entry threshold for voluntary entrepreneurship, discouraging marginal entrants. Although improved access to credit enables some talented but previously constrained involutary entrepreneurs and workers to enter voluntary entrepreneurship category, the wage-threshold effect typically dominates, resulting in a lower share of voluntary entrepreneurs at higher ϕ.

With rising wages and interest rates, less-talented individuals who previously operated as voluntary entrepreneurs may exit that category. Since their profits are squeezed by higher input costs and their access to external credit is reduced, they are more likely to shift either into wage employment (worker category) or into involuntary entrepreneurship. As a result may lead to a relative expansion in the shares of workers and involuntary entrepreneurs in the occupational distribution.

Overall, output per capita increases with rising ϕ. As credit frictions are relaxed, more productive individuals become less constrained in their ability to borrow, allowing them to operate firms at larger and more efficient scales. This reallocation of resources away from low-productivity to high-productivity agents reduces misallocation in the economy, thereby raising aggregate efficiency and boosting per-capita output. Total capital in the economy rises with increasing ϕ. On the demand side, reduced financial frictions allow firms to expand scale, raising the aggregate demand for capital. On the supply side, higher incomes translate into greater savings, which further relaxes capital constraints and expands the overall supply of assets. Together, these forces generate an increase in the total capital stock as ϕ rises.

Table 1: Impact of Changing ϕ: General Equilibrium

ϕ	**0**	**0.2**	**0.4**	**0.6**	**0.8**	**1.0**
r	0	0	0	0.03	0.06	0.07
w	1.86	2.26	2.65	3.17	3.83	3.96
Y (Output per Capita)	3.25	3.97	4.96	5.98	7.19	7.34
Y (Output per Capita - Voluntary Entrepreneurs)	3.19	3.86	4.83	5.77	7.04	7.21
Y (Output per Capita - Involuntary Entrepreneurs)	0.06	0.11	0.13	0.21	0.15	0.13
K (Capital per Capita)	2.60	3.51	5.41	8.49	14.56	15.82
L (Worker Share)	0.54	0.57	0.58	0.60	0.60	0.60
Share of Voluntary Entrepreneurs	0.12	0.08	0.07	0.04	0.04	0.04
Share of Involuntary Entrepreneurs	0.33	0.35	0.35	0.36	0.36	0.36
Mean Talent (Voluntary Entrepreneurs)	5.48	6.65	7.38	12.03	12.03	12.03

Note: For the simulations in this table, the value of and χ parameters are taken to be 0.75 and 0.62, respectively. Other parameters are set the same values as mentioned in Table 4]

2.4 Model Extension - Common Capital Market and Shared Interest Rate

To explore the implications of financial integration across states, I extend the model to a setting in which there are two states that share a common capital market—that is, they face a uniform equilibrium interest rate r, determined by the joint supply and demand for capital across both regions, while labor markets continue to clear within individual states. This setup represents a case of partial financial integration: capital markets are nationally integrated, ensuring a common price of credit across states, but enforcement institutions and production remain localized. Firms are geographically immobile—they hire labor and produce only within their home state—but they can borrow from the shared pool of credit supplied by national financial intermediaries. In this environment, savers in either state can deposit funds that are then allocated to entrepreneurs in both regions according to expected returns, equalizing the equilibrium interest rate across states.

This formulation allows credit to flow from the low-enforcement to the high-enforcement state, as weaker contract enforcement depresses the marginal return to capital locally and induces capital outflows. Consequently, the local interest rate rises in the weak-enforcement state—reflecting the scarcity of domestic funds—while it falls in the strong-enforcement state, where inflows expand credit availability and lower the cost of borrowing. Through this reallocation, capital-market integration transmits enforcement-driven shocks across states, even though firms and production remain geographically fixed. Relative to the autarkic benchmark, where each state determines its own r_s the introduction of a shared r thus generates offsetting adjustments: the weak-enforcement state experiences higher borrowing costs (higher r) and lower investment, while the strong-enforcement state benefits from an inflow of savings and a lower cost of credit (lower r). The integrated equilibrium interest rate lies between the two autarkic rates, and aggregate capital is more efficiently allocated across entrepreneurs according to enforcement quality rather than geographical boundaries.

Table **??** and 3 highlight this pattern. Table **??** reports results for the case where the partner state has very weak enforcement ($\phi_2 = 0$), whereas Table 3 reports results for the case where the partner state has very strong enforcement ($\phi_2 = 1$). On comparison with Table 1, which is the autarky case, the interest rate is systematically lower for all values of ϕ when the state has stronger enforcement vs the partner state which has very weak enforcement(Table **??**), and systematically higher for all values of ϕ when the state has weaker enforcement vs the partner state which has very strong enforcement (Table 3).

In the strong-enforcement state, cheaper access to capital enables productive entrepreneurs to expand their scale of operation, increasing both aggregate capital and output. Lower borrowing costs also encourage entry by moderately talented individuals who were previously constrained, thereby raising the share of voluntary firms but reducing the mean talent among them. The relaxation of credit constraints thus expands the extensive margin of entrepreneurship, while slightly diluting average ability at the intensive margin. Worker and involuntary entrepreneurship shares decline relative to the autarky case, as more individuals transition into voluntary production. These patterns are clearly reflected in the comparison of Table **??** with Table 1.

In contrast, in the weak-enforcement state, higher borrowing costs compress entrepreneurial profits and discourage voluntary entrepreneurship. As credit constraints tighten, a larger share of individuals remain in wage employment or move into involuntary entrepreneurship. This pattern is clearly visible in the decline in voluntary entrepreneurship and the corresponding increase in worker and involuntary entrepreneur shares in Table 3 relative to Table 1. Both capital per capita and per-capita output decline as investment contracts. Among the remaining voluntary entrepreneurs, average talent rises, as only the most productive individuals can sustain operation under higher borrowing costs—consistent with the sharper talent selection observed in Table 3 versus Table 1.

Overall, because the integrated market reallocates credit toward jurisdictions with stronger enforcement, capital and income per capita diverge across the two states, with the high-enforcement state accumulating a larger capital stock and generating higher average earnings. Output produced by voluntary entrepreneurs rises sharply in this state, while the weak-enforcement state experiences reduction in voluntary output and a rising share of involuntary entrepreneurs and workers.

3 Quantitative Analysis

In this section, I first present the calibration strategy. The key parameter of interest for explaining disparities in income across states is the degree of credit contract enforcement, ϕ, which I allow to vary across Indian states. All other model parameters are held constant across states. I outline the approach used to calibrate the common national parameters, and then the state-parameter ϕ.

In the results section, I then compare the model's predictions for key outcomes—GDP per capita and the average size of voluntary firms—with their empirical counterparts. I assess the extent to which cross-state differences in ϕ can account for the observed disparities in per capita income, and examine how the calibrated ϕ parameters relate to state-level measures of judicial efficiency. I also do a version of the calibration in which I use the state-level measures of judicial efficiency directly in the calibration exercise - this version is presented in the appendix.

3.1 Calibration

I assume that all model parameters other than ϕ are common across Indian states. These common "national" parameters are: two technology parameters α and θ; the AR(1) parameters of entrepreneurial productivity (ρ, σ); the discount factor β; the coefficient of relative risk aversion γ; the depreciation rate δ; and the labor-opportunity parameter χ. Among these, the values of γ, and δ are taken from the literature; β and ρ are set to 0.92 and 0.9 respectively, based on conventional values in the Macro literature. α and θ are directly set equal to the capital and labor income shares in India for 2017–18, based on data from the National Accounts Statistics (NAS). The parameters χ and σ are calibrated by matching model-generated moments to their empirical counterparts: specifically, χ is set to match the share of workers in the labor force[3], and σ is set to match the standard deviation of log firm size[4].[5] Table 4 reports the values of all national parameters, along with the model and data moments used for the calibrated parameters.

Table 2: National Parameters

Parameter	**Value**	**Target / Source**	**Model**	**Data**
Directly set from National Accounts (data-imposed)				
α	0.28	Capital income share in GDP (NAS 2017–18)	—	
θ	0.32	Wage income share in GDP (NAS 2017–18)	—	
Disciplined by explicit targets				
χ	0.62	Share of workers (PLFS 2017–18)	0.57	0.57
σ	0.75	SD of log firm size (ASI 2017–18)	1.3	1.5
Set from literature / Conventional values				
ρ	0.90	Conventional in macro/firm dynamics	—	
β	0.92	Buera et al. (2011)	—	
γ	1.50	Standard CRRA	—	
δ	0.06	Standard depreciation	—	

I calibrate the state-level enforcement parameter, ϕ_S, using two complementary approaches. The first approach directly maps ϕ_S from judicial efficiency data to capture institutional variation in contract enforcement across Indian states. The second approach infers ϕ_S by matching the

[3]Source: Periodic Labour Force Survey (PLFS), 2017–18

[4]Source: Annual Survey of Industries (ASI), 2017–18

[5]The target moments are matched conditional on setting the value of ϕ such that the model reproduces India's external finance-to-GDP ratio.

model-generated external finance–to–GDP ratio with its empirical counterpart and then examines its correlation with judicial efficiency indicators. Taken together, the two methods provide both a structural and a quantitative validation of the role of enforcement in shaping financial access and income disparities across states.

The calibration focuses on 21 major Indian states for which consistent data on judicial performance and bank credit are available. [6]

The measure of judicial efficiency is proxied by the average age of disposed civil suit cases in district and sessions courts across Indian states in 2018, as reported in the National Judicial Data Grid (NJDG). The NJDG compiles real-time data from courts across India, providing comprehensive information on case pendency, filing, and disposal patterns. Focusing on civil suit cases is appropriate, as these commonly involve contract and credit enforcement disputes that directly affect firms' ability to recover dues and enforce financial claims. A higher average age corresponds to slower judicial processes and weaker enforcement, while a lower value indicates faster case resolution and stronger contract enforcement.[7]

Approach 1: Judicial-Efficiency Mapping. In the baseline calibration, ϕ_S is derived from observed judicial efficiency—proxied by the average duration of civil case disposal in district and subordinate courts. The mapping follows a logistic functional form,

$$\phi(s) = \frac{1}{1 + e^{(\alpha + \beta speed)}},$$

where *speed* denotes the average age of disposed cases (in years) in 2018. Lower values of *speed* imply faster courts and hence stronger enforcement. The parameters (α, β) are pinned down by two empirical anchors: I select two representative states—one with highest judicial efficiency and one with low efficiency — and assign them target enforcement levels $(\bar{\phi}_H, \bar{\phi}_L)$ consistent with their relative positions in the data. The resulting pair (α, β) determines the implied ϕ_S for each state.[8] This procedure anchors the model in observable institutional variation and yields a state-specific measure of enforcement quality grounded in judicial performance.

The parameters $\alpha = -1.04$ and $\beta = 0.55$ are chosen such that $\phi_{\text{Haryana}} = 0.5$ at a judicial

[6] The North-Eastern states of Arunachal Pradesh, Meghalaya, Mizoram, Nagaland, Tripura, and Sikkim are excluded from the quantitative analysis because of limited coverage in industrial and judicial datasets. Their small manufacturing base, low formal credit penetration, and incomplete reporting in the National Judicial Data Grid make consistent calibration of enforcement quality and credit intensity infeasible. Union Territories, including Delhi and Jammu & Kashmir, are also excluded.

[7] District and sessions courts account for nearly 87.5 percent of all pending cases in India, making their disposal speed a representative proxy for state-level judicial efficiency.

[8] The logistic specification provides a smooth, monotonic mapping bounded on $(0, 1)$, and flexible curvature, whereas other functional forms such as exponential decay offer less control over slope and asymptotic limits.

speed of 1.89 years, and $\phi_{\text{Bihar}} = 0.1$ at a judicial speed of 5.9 years. Table B1 lists the calibrated values of ϕ_S for each state, derived from the observed average age of disposed civil cases.

Approach 2: Matching Model-Implied External Finance. As a complementary calibration, ϕ_S is also obtained by matching the model-generated ratio of external finance to GDP with its empirical counterpart for each state. In the model, aggregate external finance is defined as

$$\int (k - a) \cdot 1(k > a) \, da \, dz,$$

where $(k - a)$ represents net borrowing by an individual, and $1(k > a)$ is an indicator function equal to one when the individual borrows. Empirically, external finance is measured as the sum of credit extended by state scheduled commercial banks and regional rural banks relative to state GDP.[9] Data on bank credit and state GDP are drawn from the *RBI Handbook of Statistics on Indian States.*[10] for the year 2017–18. Table B1 reports the calibrated values of ϕ_S obtained from this approach.

3.2 Results

Table B2 reports the model-predicted outcomes for GDP per capita[11] , external finance-to-GDP, and the average size of voluntary firms across states, alongside the corresponding data for 2017–18, when model ϕ_S are calibrated under Approach 1 (ϕ_S calibrated directly from observed judicial efficiency, proxied by the average duration of civil case disposal). Firm size is measured by the number of workers employed per establishment. Firms reported in the Annual Survey of Industries (ASI) are treated as representative of voluntary, entrepreneur-owned firms.[12]. External finance-to-GDP is measured as the sum of credit extended by state scheduled commercial banks and regional rural banks relative to state GDP in the data. Figures B1, B2a, and B2b display scatter plots of the data against the model-predicted values for per capita output, external finance-to-GDP, and the average size of voluntary firms, respectively.

[9] This sum serves as the empirical counterpart of external finance available at the state level in India. Other potential sources of external finance include non-banking financial companies (NBFCs), cooperative banks, and capital-market instruments such as bonds or debentures. However, comparable state-level data for these sources are not systematically available, and hence the measure is restricted to bank credit from scheduled commercial and regional rural banks.

[10] Link:`https://m.rbi.org.in/Scripts/AnnualPublications.aspx?head=Handbook+of+Statistics+on+Indian+States`

[11] State-level GDP data are drawn from the RBI Handbook of Statistics on Indian States.

[12] The Annual Survey of Industries (ASI) covers registered manufacturing establishments under the Factories Act, 1948—units employing 10 or more workers with power or 20 or more without power. These firms hire labor, maintain accounts, and operate at commercial scale, making them a suitable empirical proxy for "voluntary entrepreneur" firms in the model. In contrast, own-account and household enterprises below these thresholds, typically representing subsistence self-employment, are covered in the National Sample Survey (NSS) unorganized-sector rounds.

To quantify the contribution of credit contract enforcement in explaining disparities in income across Indian states, I regress the data on GDP per capita against the model-predicted GDP per capita. The resulting positive relationship and an R-squared of 0.06 indicates that differences in ϕ—the degree of credit contract enforcement—accounts for approximately 6 percent of the variation in GDP per capita across states.

As a validation exercise, I examine the relationship between the model-implied ratio of external finance to GDP and firm sizes to their empirical counterparts across states under Approach 1. As seen in Figure B2a and B2b, the correlation is positive, indicating that the calibration successfully reproduces cross-state variation in financial depth observed in the data. This suggests that the enforcement heterogeneity embedded in the calibrated ϕ_S parameters is economically meaningful and consistent with observed credit availability. Similarly, a regression of the data on average firm sizes against the model-predicted firm sizes shows a positive relationship and yields an R-squared of 0.072, validating the model predictions of firm sizes.

The model's quantitative results are consistent with its core mechanism linking credit contract enforcement to aggregate productivity through the easing of borrowing constraints and the reallocation of resources. Higher values of the enforcement parameter relax collateral constraints faced by productive but asset-poor entrepreneurs, enabling them to operate at larger scales and expand output. This process raises average firm size and aggregate income, as reflected in the positive association between model-predicted and observed GDP per capita across states. At the same time, stronger enforcement generates general-equilibrium feedbacks: higher wages and interest rates—driven by greater demand for labor and capital—alter firm's entry and scale decisions. More productive entrepreneurs expand as borrowing constraints loosen, while marginal or low-productivity firms contract or exit in response to higher input costs. The resulting reallocation shifts resources toward larger, more efficient enterprises, raising aggregate productivity even without an increase in the total number of firms. Accordingly, states with stronger enforcement and faster judicial systems exhibit both higher per-capita output and larger firm sizes in the data, and the positive correlation between model-implied and observed external-finance-to-GDP ratios further validates the calibration and its mechanism.

When the model is solved using the calibrated parameters under Approach 2, the results closely mirror those obtained under Approach 1. A regression of observed state-level GDP per capita on the model-predicted values yields an R-squared of 0.035, suggesting that cross-state differences in ϕ the degree of credit contract enforcement—account for approximately 3.5 percent of the variation in income per capita. Likewise, the correlation between model-implied and observed average firm sizes is positive, reinforcing the consistency of the calibration with empirical patterns and confirming that the enforcement mechanism captures meaningful cross-state heterogeneity in both output and firm size. (See figures B3 and B4a)

I further assess the relationship between the model-calibrated, state-level ϕ parameters and the average age of disposed civil suit cases in district and session courts in 2018. Table B5 reports state-wise data on the average age of disposed cases, and Figure B4b plots the calibrated ϕ values against the reciprocal of this measure (used as an index of judicial speed). Their is a positive correlation of 0.26 between the two.The correlation between the two is positive (0.26), indicating that states with faster judicial processes tend to exhibit higher calibrated enforcement parameters, consistent with the interpretation ϕ_S of as capturing the strength of credit contract enforcement.[13]

While the overall patterns under Approaches 1 and 2 are broadly similar, minor differences arise from the distinct calibration sources for the enforcement parameter. In Approach 1, ϕ_S is directly mapped from observed judicial efficiency, capturing institutional heterogeneity in the speed and reliability of credit contract enforcement. In contrast, Approach 2 infers ϕ_S by matching the model-generated external-finance-to-GDP ratio to its empirical counterpart. Since the empirical measure of external finance is restricted to bank credit—excluding other channels such as non-banking financial institutions, cooperative credit, and capital-market instruments—it may not fully capture the underlying enforcement environment. Consequently, the distribution of ϕ_S and its explanatory power for income variation differ slightly across the two approaches. Nonetheless, the strong qualitative consistency of results across both exercises underscores the robustness of the model's central mechanism linking effective credit contract enforcement to improved allocation and aggregate productivity.

4 Judicial Speed and Occupational Choice: Empirical Evidence

This section provides empirical evidence on the effect of judicial enforcement on individual's occupational choices. The speed of resolution of civil cases by courts serves as a practical and observable proxy for the enforcement of credit contracts. I employ a difference-in-differences (DiD) strategy that exploits cross-state variation in implementation of the 2002 Code of Civil Procedure (CPC) Amendment Act, following Chemin (2012). The reform introduced procedural changes intended to accelerate civil litigation in India, and its effects are expected to apply to credit contract disputes,

[13] Judicial speed serves as the primary determinant of credit contract enforcement, as faster case resolution directly strengthens the credibility and timeliness of legal recourse available to lenders. Nevertheless, enforcement outcomes also depend on complementary institutional features—such as the effectiveness of judgment execution, local governance quality, and the presence of informal enforcement networks—as well as credit-market characteristics like banking depth, information infrastructure, and lender competition. Together, these elements influence the overall ease of enforcing credit contracts and accessing finance across Indian states.

which are adjudicated in the same civil courts.

Subsection 4.1 describes the characteristics and definitions of the three occupation types. Subsection 4.2 outlines the identification strategy. Subsection 4.3 details the datasets and variable construction. Subsection 4.3 presents the empirical model. Subsection 4.5 reports the regression results.

4.1 Occupation Type Categorization

In this subsection, I discuss the definitions and key characteristics of the three occupation types: voluntary entrepreneurs, involuntary entrepreneurs, and workers.

Voluntary entrepreneurs are the traditional entrepreneurs—the epitome of "modern capitalist development", the "agents of innovation", the disruptive economic leaders (Schumpeter (1911)) who undertake costly and risky investments (Knight (1921)) and develop new goods, services, and production processes (Schumpeter (1911)). They shape the productivity of firms (Murphy et al. (1991)), facilitate economic growth and create jobs.

The notion of involuntary entrepreneurship builds on Lewis's mid-1950s account of surplus labor in developing economies, where many individuals engaged in low-productivity self-employment due to limited alternatives. Tokman (2007) similarly argues that such entrepreneurship reflects "a failure of the economic system to create enough productive employment," suggesting that many would prefer salaried jobs if available. Empirical evidence from De Mel et al. (2010) shows that these entrepreneurs have significantly lower ability and cognitive skill scores than owners of larger firms, highlighting their relatively low human capital.

The third occupational category is worker, defined as individuals employed in the enterprises of others and earning a fixed wage or salary in return for their labor.

4.2 Identification Strategy

To identify the impact of judicial speed on individuals' occupational choices, I follow the empirical strategy proposed by Chemin (2012), exploiting cross-state variation in exposure to the 2002 Civil Procedure Code (CPC) Amendment Act in India. The CPC, originally enacted in 1908, is the main procedural law governing civil litigation and thus the resolution of most credit contract disputes. The 2002 amendment introduced a series of procedural reforms intended to accelerate civil case processing, including tighter time limits at various stages of proceedings, restrictions on adjournments, and expanded use of alternative dispute resolution mechanisms.

Although the Act applied nationally, its net effect on court procedures differed across states because individual states had previously amended specific CPC orders and rules at different points in time. Some states had already adopted provisions similar to those in the 2002 reform, while others had not. As a result, states received different "policy doses" when the national amendment was implemented. Following Chemin (2012), I summarize this heterogeneity in a state-level treatment-intensity index that captures how much each state was newly exposed to the reform.

Intuitively, states that had not pre-adopted many of the speed-enhancing provisions experienced a larger improvement in judicial efficiency when the 2002 Act came into force, while states that had already implemented similar amendments experienced a smaller change. The empirical identification relies on a difference-in-differences design in which this state-level treatment intensity is interacted with post-reform indicators. The resulting DiD coefficients trace how improvements in judicial speed, interpreted as stronger credit contract enforcement, affect the probabilities of being a voluntary entrepreneur, an involuntary entrepreneur, or a worker. Full details on the construction of the treatment-intensity index and the underlying amendment coding are provided in Appendix C.

4.3 Data and Variable Construction

The empirical analysis uses individual-level data from three rounds of the Employment and Unemployment Surveys of the National Sample Survey (NSS): the 50th (1993–94), 55th (1999–2000), and 61st (2004–2005) rounds. These nationally representative surveys provide detailed information on individual's employment status, demographic characteristics, and enterprise activity. The data consist of repeated cross-sections rather than a panel. The 55th and 61st rounds serve as the pre- and post-reform periods surrounding the 2002 Civil Procedure Code Amendment Act. The 50th round is used to assess pre-reform trends. The sample is restricted to working-age individuals engaged in non-agricultural activities. Individuals classified as unpaid family workers, unemployed, or not in the labor force are excluded.

Occupational outcomes are constructed using the NSS activity-status classifications. Individuals whose principal activity status is *employer*—defined as those who run their own enterprise (alone or with partners) and primarily operate it by hiring labor—are classified as *voluntary entrepreneurs*. Those classified as *own-account workers*, who operate their own enterprises but typically do so without hiring labor, are classified as *involuntary entrepreneurs*. Economically, this classification maps naturally into the model's distinction between opportunity-driven and necessity-driven entrepreneurship: employers are more likely to have entered entrepreneurship to exploit business opportunities and operate at a larger scale with hired labor, whereas own-account workers typically engage in self-employment due to limited wage-employment options, with low capital intensity and minimal labor hiring, making their activities closer to subsistence employment. *Workers* are defined as individuals employed in the enterprises of others and receiving a fixed wage or salary; both regular and casual wage earners are grouped into this category.

The dependent variable is a categorical indicator taking three values corresponding to involuntary entrepreneurs, voluntary entrepreneurs, and workers. Individual-level controls include education, age, gender, marital status, religion, and social group. Education is constructed as an ordinal categorical variable ranging from 1 to 6, with higher values corresponding to higher levels of educational attainment and a greater number of years of schooling. [14] In addition to state fixed effects, the empirical specifications include time-varying state-level controls to account for concurrent institutional and economic changes, drawn from the RBI Handbook of Statistics on Indian States. To account for alternative channels of dispute resolution that may affect court congestion and case disposal independently of the CPC reform, I also include measures of the intensity of cases resolved through Lok Adalats (people's courts), obtained from data.gov.in.

4.4 Occupational Choice Regressions

I estimate a difference-in-differences specification that exploits cross-state variation in exposure to the 2002 CPC Amendment Act and time variation across NSS survey rounds. Identification comes from interacting a state-specific treatment-intensity index with post-reform indicators, allowing the effect of improved judicial speed to vary across states. This strategy is implemented using multinomial logit regressions of the following form:

$$\begin{aligned}\ln\left(\frac{p_{Jist}}{p_{Wist}}\right) &= \alpha_{J0} + \alpha_{Js} + \lambda_J^{1994}\, 1994_t + \lambda_J^{2005}\, 2005_t \\ &\quad + \beta_J^{1994}\,(1994_t \times 2002AmendmentAct_s) + \beta_J^{2005}\,(2005_t \times 2002AmendmentAct_s) \\ &\quad + \gamma_J\, edu_{ist} + \mathbf{x}_{ist}\delta_J + \mathbf{d}_{st}\eta_J + \varepsilon_{ist}.\end{aligned} \tag{16}$$

The multinomial logit framework is appropriate because individuals are classified into a single principal occupation in the NSS, making voluntary entrepreneurship, involuntary entrepreneurship, and wage work mutually exclusive outcomes. This framework allows enforcement-induced shifts to be estimated jointly across the three occupational choices.

In equation (18), the subscript J denotes either voluntary or involuntary entrepreneurship, while W denotes wage work; i indexes individuals, s states, and t time. Wage work is the omitted base category, so coefficients are interpreted relative to employment as a worker. The term p_{Jist}

[14] Education is coded as a categorical variable from 1 to 6 (1 = not literate; 2 = below primary school; 3 = primary and middle school; 4 = secondary education; 5 = higher secondary education; 6 = graduate and above)

denotes the probability that individual i in state s at time t chooses occupation J, and p_{Wist} the probability of choosing wage work. The dependent variable, $\ln(p_{Jist}/p_{Wist})$, therefore represents the log odds of choosing voluntary (or involuntary) entrepreneurship rather than wage employment.

The term α_{J0} is an intercept, while α_{Js} captures unobserved, time-invariant state-level heterogeneity (state fixed effects). The base year is 2000. The indicator variables 1994_t and 2005_t equal one in the corresponding NSS survey rounds and zero otherwise, and capture common time shocks relative to the base year. The variable $2002AmendmentAct_s$ is the state-level treatment-intensity index associated with the 2002 CPC Amendment Act, constructed as described in Section 4.2. The coefficient β_J^{2005} on the interaction $2005_t \times 2002AmendmentAct_s$ identifies the causal effect of a one-unit increase in judicial speed on the log odds of choosing voluntary entrepreneurship (or involuntary entrepreneurship) relative to wage work. The interaction $1994_t \times 2002AmendmentAct_s$ serves as a placebo test for pre-trends; a statistically insignificant coefficient supports the parallel-trends assumption underlying the difference-in-differences design.

The regressions include the education measure edu_{ist} and a vector of individual-level controls $\mathbf{x}_{ist}$, as defined in Section 4.3, along with indicators for sector of employment. Time-varying state-level controls $\mathbf{d}_{st}$ are included to absorb concurrent state-level changes that may affect occupational choice. To account for variation in alternative dispute resolution outside the formal court system, $\mathbf{d}_{st}$ includes the per capita number of cases disposed by Lok Adalats at the state level, as well as the growth rate of state-level net domestic product per capita. Standard errors are clustered at the state level to allow for serial correlation in treatment exposure within states over time.

4.5 Results

4.5.1 Summary Statistics

Table 3 reports summary statistics for the main outcome and explanatory variables in the pre-reform (2000) and post-reform (2005) periods, separately for low- and high-dose states. Low-dose states are those with treatment-intensity scores between 34 and 37 under the 2002 CPC Amendment Act, while high-dose states have scores between 38 and 40.

Across both periods and state groups, voluntary entrepreneurs constitute a small share of the non-agricultural workforce (around 2 percent), while involuntary entrepreneurs account for a substantially larger fraction (roughly 30–40 percent). Wage workers comprise the majority of the workforce, representing approximately 55–70 percent of individuals.[15] Educational attainment is low on average, with most individuals having completed no more than primary or middle school.

[15] Wage workers are roughly evenly split between regular and casual employment.

Female labor force participation is limited, with women accounting for less than 20 percent of the working population in the sample. These patterns are consistent across low- and high-dose states in both the pre- and post-reform periods.

Table 3: Summary Statistics

Year	2000		2005	
	High Dose (38–40)	Low Dose (34–37)	High Dose (38–40)	Low Dose (34–37)
Voluntary Firm Owner	0.0139	0.0096	0.0173	0.0151
	(0.117)	(0.098)	(0.130)	(0.122)
Involuntary Firm Owner	0.317	0.383	0.349	0.409
	(0.465)	(0.486)	(0.477)	(0.492)
Workers	0.669	0.607	0.633	0.576
	(0.471)	(0.488)	(0.482)	(0.494)
Education	3.377	3.329	3.388	3.337
	(1.580)	(1.698)	(1.617)	(1.693)
Sex	0.819	0.882	0.806	0.870
	(0.385)	(0.323)	(0.396)	(0.336)

Note: Standard deviations are reported in parentheses.
States are grouped into low- and high-dose categories for descriptive purposes. The regression analysis exploits cross-state variation in a continuous treatment-intensity index associated with the 2002 CPC Amendment Act.

4.6 Regression Results

Table 4 reports the marginal effects estimated from multinomial logit regressions of occupational choice on the interaction between the 2002 Amendment Act's state-level impact measure and the post-reform (2005) and pre-reform (1994) periods. Columns (1)–(2) present results for voluntary entrepreneurs (employers), columns (3)–(4) for involuntary entrepreneurs (own-account workers), and columns (5)–(6) for workers. Odd-numbered columns exclude state-level controls, while even-numbered columns include them. All specifications control for individual characteristics (education, age, sex, marital status, religion, and social group), sector controls, state fixed effects, and a common time effect.

The coefficient on the interaction term $2005_t \times 2002AmendmentAct_s$ captures the effect of improvements in judicial enforcement on occupational choice. The estimated marginal effects indicate that states experiencing larger improvements in judicial efficiency exhibit a statistically significant decline in voluntary entrepreneurship and a corresponding increase in involuntary entrepreneurship. Quantitatively, a one-unit increase in the policy dose is associated with a 0.27–0.33 percentage point reduction in the probability of being a voluntary entrepreneur and an increase of approximately 0.23 percentage points in the probability of being an involuntary entrepreneur. The marginal effect for wage work is positive but relatively small and statistically insignificant.

Table 4: Marginal Effects of Judicial Speed on Occupational Choice (Multinomial Logit)

	Voluntary Entrepreneur (Employer)		Involuntary Entrepreneur (Own-Account Type)		Worker	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Post-Reform						
(2005 · 2002AmendmentAct)	-0.0027***	-0.0030***	0.0023	0.0023	0.0004	0.0006
	(0.0009)	(0.0011)	(0.0054)	(0.0054)	(0.0056)	(0.0057)
Panel B: Pre-Reform (Placebo)						
(1994 · 2002AmendmentAct)	-0.0027	-0.0030	0.0041	0.0040	-0.0014	-0.0010
	(0.0019)	(0.0022)	(0.0047)	(0.0050)	(0.0052)	(0.0059)
Edu	0.0051***	0.0051***	-0.0401***	-0.0401***	0.0350***	0.0350***
	(0.0002)	(0.0002)	(0.0025)	(0.0025)	(0.0025)	(0.0025)
Time, State FE	Yes	Yes	Yes	Yes	Yes	Yes
Indiv Controls	Yes	Yes	Yes	Yes	Yes	Yes
State-level Controls	No	Yes	No	Yes	No	Yes
Sector Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	286165	286165	286165	286165	286165	286165
Pseudo R^2	0.0804	0.0809	0.0804	0.0809	0.0804	0.0809

Note: Reported coefficients are average marginal effects on the probability of choosing each occupation.
Standard errors in parentheses. Significance: $^{*}p < .1$, $^{**}p < .05$, $^{***}p < .01$.
Standard errors are clustered at the state level.

Although these marginal effects are modest in magnitude, they imply economically meaningful reallocations when aggregated over India's large working-age population. The pre-reform interaction $1994_t \times 2002AmendmentAct_s$ is statistically insignificant across all occupational categories, providing no evidence of differential pre-trends and supporting the validity of the difference-in-differences design. Education has a strong and statistically significant association with occupational choice: higher educational attainment increases the likelihood of voluntary entrepreneurship and reduces the likelihood of involuntary entrepreneurship. This pattern is consistent with education proxying for individual skill or ability that facilitates operation at larger firm scale

Overall, the empirical results are consistent with the model's predictions. In the model, improvements in judicial enforcement raise equilibrium wages and borrowing costs, making marginal voluntary entrepreneurship less profitable while enabling the most productive firms to expand. The observed shift away from voluntary entrepreneurship toward own-account self-employment and wage work is therefore consistent with the transitional reallocation dynamics implied by improved credit enforcement.

5 Conclusion

This paper develops and quantifies a general equilibrium framework to evaluate the role of credit contract enforcement in shaping income disparities across Indian states. The model introduces heterogeneous agents who fall in occupational categories of voluntary entrepreneurship, involuntary entrepreneurship, or wage work, subject to credit enforcement and labor market frictions. State-specific enforcement capacity governs the extent of borrowing constraints, thereby determining the scale of firm operations and the allocation of resources across production units.

Quantitatively, the calibrated model reproduces key cross-state patterns in GDP per capita and firm size distributions. Differences in the degree of credit contract enforcement explain about 6.5 percent of the variation in income per capita across Indian states in 2017–18. States with higher model-implied enforcement parameters also exhibit faster judicial systems, as measured by the speed of resolution of civil cases, confirming that the calibration captures meaningful institutional variation. The model's general equilibrium mechanisms imply that stronger enforcement relaxes credit constraints for productive but asset-poor entrepreneurs, leading to reallocation toward larger and more efficient firms, higher wages, and greater aggregate output.

The common-capital-market extension demonstrates that partial financial integration can widen income gaps: high-enforcement states benefit from lower borrowing costs and higher productivity, whereas low-enforcement states face rising interest rates and reduced entrepreneurial activity.

These spillovers suggest that improving enforcement institutions remains essential not only for local development but also to prevent divergence in an integrated economy.

The empirical analysis corroborates these mechanisms using microdata from three rounds of the National Sample Survey Employment and Unemployment Surveys (1993–94, 1999–2000, and 2004–05) and exploiting cross-state variation in the implementation of the 2002 Civil Procedure Code Amendment Act. The multinomial logit regressions show that improvements in judicial efficiency reduce the likelihood of voluntary entrepreneurship, while increasing the likelihood of on involuntary entrepreneurship and wage work, although the later results are insignificant. Together, the empirical results validate the model's prediction that improvements in enforcement tighten the entry margin for entrepreneurship and increase the average quality of entrepreneurs.

Overall, the findings demonstrate that institutional quality in credit markets—specifically, the effectiveness of contract enforcement—has measurable implications for occupational allocation, resource efficiency, and income disparities. Strengthening the enforcement of credit contracts, through judicial and procedural reforms that accelerate dispute resolution, can thus enhance the productivity of entrepreneurship and narrow regional income gaps. Future work could extend this framework to incorporate dynamic policy reforms, heterogeneity in informal credit enforcement, and interactions with labor and land market frictions to better capture the multifaceted nature of institutional development in emerging economies like India.

Appendix

A Tables from model extension with common capital market

Table A1: Impact of changing ϕ_1 on State 1 outcomes: 2 states case, common capital market, GE, $\phi_2 = 0$ (State 1 has stronger enforcement vs State 2, State 2's ϕ_2 is fixed)

ϕ_1	**0**	**0.2**	**0.4**	**0.6**	**0.8**	**1.0**
r	0	0	0	0	0.04	0.05
w	1.83	2.16	2.50	3.16	3.83	4.16
Y (Output per Capita)	3.29	4.14	5.19	6.22	7.67	7.94
Y (Output per Capita - Voluntary Entrepreneurs)	3.24	4.07	5.06	5.98	7.50	7.92
Y (Output per Capita - Involuntary Entrepreneurs)	0.05	0.07	0.13	0.24	0.17	0.15
K (Capital per Capita)	2.64	3.69	5.63	9.40	17.52	20.21
L (Worker Share)	0.54	0.55	0.57	0.60	0.60	0.60
Share of Voluntary Entrepreneurs	0.13	0.11	0.08	0.04	0.04	0.04
Share of Involuntary Entrepreneurs	0.33	0.34	0.35	0.37	0.37	0.37
Mean Talent (Voluntary Entrepreneurs)	5.37	5.79	6.91	12.03	12.03	12.03

Table A2: Impact of changing ϕ_1 on State 1 outcomes: 2 states case, common capital market, GE, $\phi_2 = 1$ (State 1 has weaker enforcement vs State 2, State 2's ϕ_2 is fixed)

ϕ_1	**0**	**0.2**	**0.4**	**0.6**	**0.8**	**1.0**
r	0.05	0.05	0.06	0.06	0.07	0.07
w	1.99	2.25	2.52	3.17	3.70	3.96
Y (Output per Capita)	3.19	3.75	4.83	5.79	7.17	7.34
Y (Output per Capita - Voluntary Entrepreneurs)	3.13	3.54	4.62	5.62	7.02	7.20
Y (Output per Capita - Involuntary Entrepreneurs)	0.06	0.20	0.21	0.17	0.15	0.14
K (Capital per Capita)	2.19	2.52	4.32	7.85	13.85	15.82
L (Worker Share)	0.55	0.60	0.60	0.60	0.60	0.60
Share of Voluntary Entrepreneurs	0.11	0.04	0.04	0.04	0.04	0.04
Share of Involuntary Entrepreneurs	0.34	0.36	0.36	0.36	0.36	0.36
Mean Talent (Voluntary Entrepreneurs)	5.66	12.03	12.03	12.03	12.03	12.03

B Tables and Figures from Quantitative Analysis

B.1 Tables and Figures from Calibration Approach 1

B.1.1 Tables

Table B1: Mapping State-Level Judicial Speed to Enforcement Parameter (ϕ_S) - (Approach 1)

State	**Avg. Age of Disposed Cases (yrs.)**	ϕ_S
Andhra Pradesh	2.81	0.38
Assam	2.48	0.42
Bihar	5.90	0.10
Chhattisgarh	4.80	0.17
Goa	4.25	0.22
Gujarat	5.31	0.13
Haryana	1.89	0.50
Himachal Pradesh	2.65	0.40
Jharkhand	5.00	0.15
Karnataka	3.14	0.34
Kerala	2.16	0.46
Madhya Pradesh	2.80	0.38
Maharashtra	3.91	0.25
Odisha	4.27	0.21
Punjab	2.26	0.45
Rajasthan	4.36	0.21
Tamil Nadu	3.04	0.35
Telangana	3.56	0.29
Uttar Pradesh	4.83	0.17
Uttarakhand	2.85	0.37
West Bengal	5.26	0.14

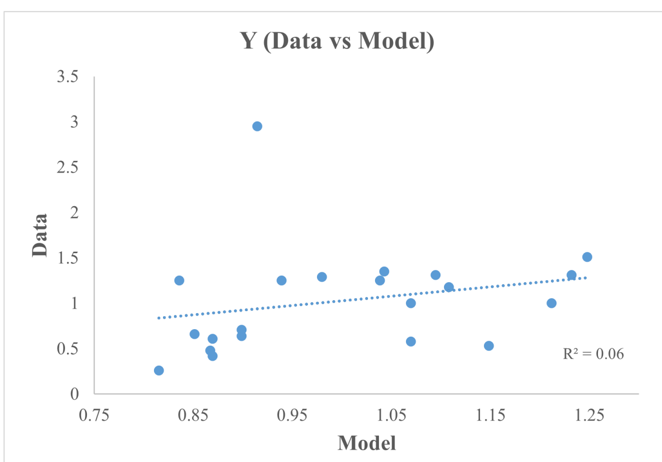
Table B2: Model-Predicted Outcomes vs Data (Approach 1)

State	ϕ_S	Y^*_{Model}	Y^*_{Data}	External Finance/ GDP (Model)	Bank Credit (Commercial + Regional Rural) / GDP (Data)	Avg. voluntary Firm Size* (Model)	Avg. voluntary Firm Size* (Data - ASI)
Andhra Pradesh	0.38	1.07	1.00	0.57	0.42	1.09	0.80
Assam	0.42	1.15	0.53	0.65	0.21	1.10	0.49
Bihar	0.10	0.82	0.26	0.12	0.25	0.61	0.39
Chhattisgarh	0.17	0.87	0.61	0.22	0.31	0.72	0.90
Goa	0.22	0.91	2.95	0.29	0.25	0.95	0.99
Gujarat	0.13	0.84	1.25	0.17	0.37	0.67	1.16
Haryana	0.50	1.25	1.51	0.88	0.34	2.43	1.35
Himachal Pradesh	0.40	1.11	1.18	0.61	0.20	1.16	0.82
Jharkhand	0.15	0.87	0.48	0.19	0.21	0.62	1.05
Karnataka	0.34	1.04	1.35	0.49	0.45	1.06	1.33
Kerala	0.46	1.23	1.31	0.74	0.43	1.11	0.61
Madhya Pradesh	0.38	1.07	0.58	0.59	0.32	1.09	0.96
Maharashtra	0.25	0.94	1.23	0.34	1.03	0.99	1.06
Odisha	0.21	0.90	0.64	0.28	0.25	0.94	1.41
Punjab	0.45	1.21	1.00	0.72	0.48	1.11	0.89
Rajasthan	0.21	0.90	0.71	0.28	0.33	0.94	0.89
Tamil Nadu	0.35	1.04	1.25	0.72	0.56	1.05	1.18
Telangana	0.29	0.98	1.29	0.28	0.62	1.03	1.17
Uttar Pradesh	0.17	0.87	0.42	0.53	0.30	0.72	0.80
Uttarakhand	0.37	1.09	1.31	0.53	0.21	1.09	1.66
West Bengal	0.14	0.85	0.66	0.53	0.39	0.62	1.12

Notes: *Re-scaled values, mean value set to 1.
Calibrated ϕ_S from logistic fit using Bihar (low) and Haryana (high) as reference points.

B.1.2 Figures

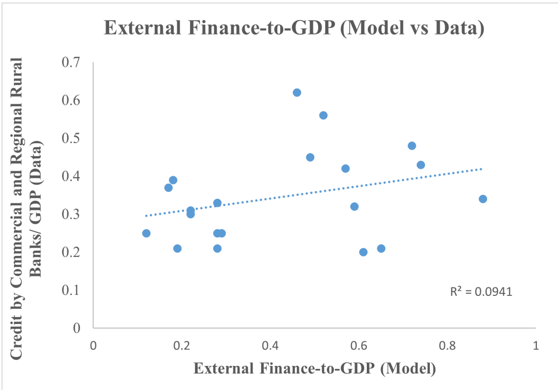
Figure B1: Predicted vs Observed Output per capita (Approach 1)



Note: Values on both axis are re-scaled, mean set to 1

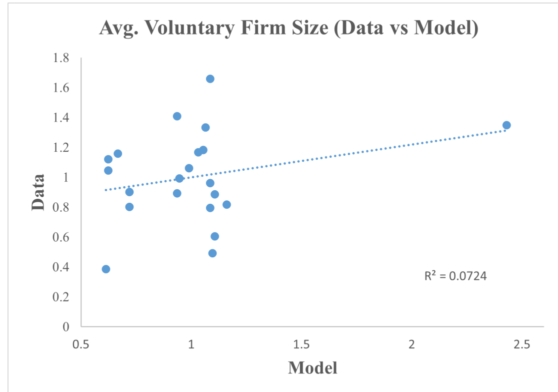
Figure B2: Predicted vs Observed Credit-to-GDP and Voluntary Firm Size (Approach 1)

(a) Predicted vs Observed Credit-to-GDP



Note: Maharashtra, identified as an outlier with a disproportionately high credit-to-GDP ratio due to the concentration of national headquarters and financial institutions, has been excluded from this scatter plot.

(b) Predicted vs Observed Avg. Voluntary Firm Size



Note: Values on both axes are re-scaled, mean set to 1.

B.2 Tables and Figures from Calibration Approach 2

B.2.1 Tables

Table B3: Calibrated ϕ_S (Approach 2)

State	Data Moment (Ext. Fin/GDP)	Model Moment (Ext. Fin/GDP)	ϕ_S
Andhra Pradesh	0.42	0.42	0.30
Assam	0.21	0.21	0.16
Bihar	0.25	0.25	0.19
Chhattisgarh	0.31	0.31	0.23
Goa	0.25	0.25	0.19
Gujarat	0.37	0.37	0.27
Haryana	0.34	0.34	0.25
Himachal Pradesh	0.20	0.20	0.15
Jharkhand	0.21	0.21	0.16
Karnataka	0.45	0.45	0.31
Kerala	0.43	0.43	0.30
Madhya Pradesh	0.32	0.32	0.24
Maharashtra	1.03	1.03	0.56
Odisha	0.25	0.25	0.19
Punjab	0.48	0.48	0.33
Rajasthan	0.33	0.33	0.24
Tamil Nadu	0.56	0.56	0.38
Telangana	0.62	0.62	0.40
Uttar Pradesh	0.30	0.30	0.22
Uttarakhand	0.21	0.21	0.16
West Bengal	0.39	0.39	0.26

Table B4: Data vs. Model-Predicted Outcomes (Approach 2)

State	Y^*_{Model}	Y^*_{Data}	**Avg. voluntary Firm Size* (Model)**	**Avg. voluntary Firm Size* (Data)**
Andhra Pradesh	1.05	1.00	1.11	0.80
Assam	0.89	0.53	0.87	0.49
Bihar	0.95	0.26	0.81	0.39
Chhattisgarh	0.98	0.61	1.00	0.90
Goa	0.95	2.95	0.81	0.99
Gujarat	1.02	1.25	1.09	1.16
Haryana	0.98	1.51	1.11	1.35
Himachal Pradesh	0.91	1.18	0.70	0.82
Jharkhand	0.89	0.48	0.87	1.05
Karnataka	1.06	1.35	1.12	1.33
Kerala	1.05	1.31	1.11	0.61
Madhya Pradesh	0.99	0.58	1.02	0.96
Maharashtra	1.37	1.23	2.64	1.06
Odisha	0.95	0.64	0.81	1.41
Punjab	1.07	1.00	1.18	0.89
Rajasthan	0.99	0.71	1.02	0.89
Tamil Nadu	1.12	1.25	1.21	1.18
Telangana	1.16	1.29	1.22	1.17
Uttar Pradesh	0.96	0.42	1.06	0.80
Uttarakhand	0.89	1.31	0.87	1.66
West Bengal	1.00	0.66	1.08	1.12

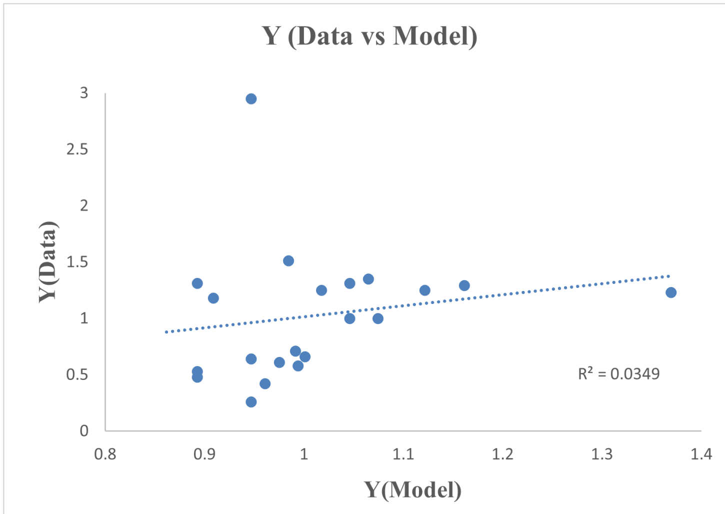
Notes: *Re-scaled values, median State value set to 1.

Table B5: State-level Data on Judicial Speed and Calibrated ϕ_S (Approach 2)

State	ϕ_S	**Avg. Age of Disposed Cases (yrs.)**
Andhra Pradesh	0.30	2.81
Assam	0.16	2.48
Bihar	0.19	5.90
Chhattisgarh	0.23	4.80
Goa	0.19	4.25
Gujarat	0.27	5.31
Haryana	0.25	1.89
Himachal Pradesh	0.15	2.65
Jharkhand	0.16	5.00
Karnataka	0.31	3.14
Kerala	0.30	2.16
Madhya Pradesh	0.24	2.80
Maharashtra	0.56	3.91
Odisha	0.19	4.27
Punjab	0.33	2.26
Rajasthan	0.24	4.36
Tamil Nadu	0.38	2.98
Telangana	0.40	3.56
Uttar Pradesh	0.22	4.83
Uttarakhand	0.16	2.85
West Bengal	0.26	5.26

B.2.2 Figures

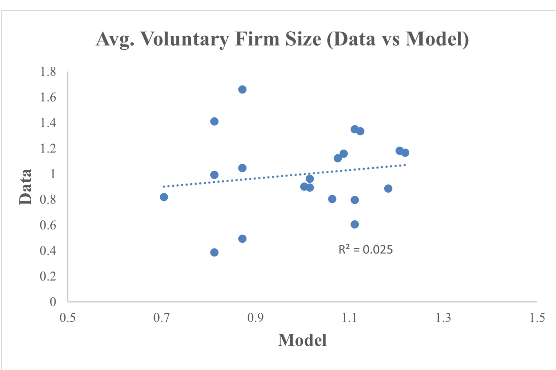
Figure B3: Predicted vs Observed Output per capita (Approach 2)



Note: Values on both axis are re-scaled, mean set to 1

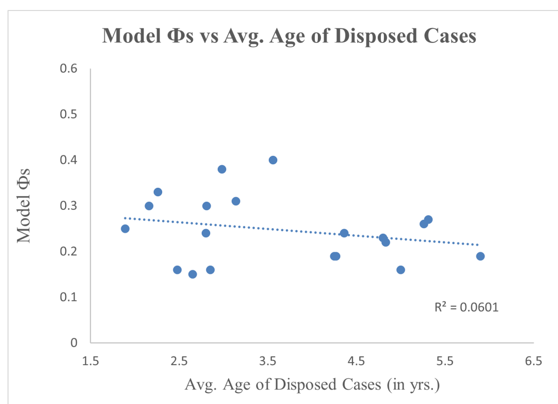
Figure B4: Predicted vs Observed Firm Size and Calibrated (ϕ_S) vs Judicial Speed (Approach 2)

(a) Predicted vs Observed Avg. Voluntary Firm Size (Approach 2)



Note: Maharashtra, identified as an outlier with a disproportionately high credit-to-GDP ratio due to the concentration of national headquarters and financial institutions, and therefore having a disproportionately high calibrated (ϕ_S), has been excluded from this scatter plot.

(b) Model Calibrated (ϕ_S) vs State-Level Judicial Speed (Approach 2)



Note: Values on both axes are re-scaled (mean = 1). Maharashtra is excluded for the same reason as in Panel (a).

C Empirical Appendix: Judicial Reform and Treatment Intensity

This appendix provides additional details on the 2002 Civil Procedure Code (CPC) Amendment Act and on the construction of the state-level treatment-intensity measure used in Section 4.2.

The 2002 CPC Amendment Act introduced 88 amendments to the CPC affecting the functioning of civil courts across all Indian states.[16] Many of these changes were designed to accelerate case processing and reduce procedural delays. Examples include: (i) prescribing time limits for serving summons on defendants; (ii) empowering courts to refer disputes to alternative dispute resolution mechanisms such as Lok Adalats, arbitration, conciliation, and mediation; (iii) imposing mandatory time limits at various stages of litigation; (iv) restricting the number of permissible adjournments; and (v) modifying the scope for appeals.

Chemin (2012) evaluates each of the 88 amendments and identifies a subset that is likely to affect court speed. Each amendment is assigned a value of $+1$ if it is expected to accelerate case disposal and -1 if it is expected to slow proceedings. Summing across all speed-relevant amendments yields the total effect of the 2002 Act for a state that had not previously modified the corresponding CPC provisions (the "baseline" state).

Indian states have the authority to amend the CPC within their jurisdiction. In practice, several states modified specific orders and rules before 2002, sometimes decades earlier. These pre-2002 amendments often overlapped with provisions later introduced at the national level by the 2002 Act. As a result, the net effect of the national reform differed across states.

To construct a state-level treatment-intensity index, Chemin (2012) starts from the aggregate speed score for the hypothetical baseline state and then adjusts it for each actual state on the basis of its pre-2002 amendments:

- If a state had already enacted the *exact same* amendment as the 2002 Act for a given order–rule pair, that amendment does not generate a marginal change in 2002, and the corresponding score is subtracted from the baseline total for that state.
- If a state had enacted a *similar but not identical* amendment, the score is adjusted to reflect only the incremental effect of the 2002 provision relative to the pre-existing state rule.
- If a state had not amended the relevant order or rule prior to 2002, it retains the full score associated with that amendment.

As an illustration from Chemin (2012), Order 20, Rule 1 of the Code of Civil Procedure specifies the timeline for pronouncing judgments after the close of hearings. The 2002 Amendment

[16] See Chemin (2012) for a full legal discussion.

Act changed this limit from 15 days (30 days in exceptional circumstances) to 30 days (60 days in exceptional circumstances). For a state that had not previously modified this rule, the amendment was coded as -1, as it lengthens the time allowed for delivering judgments and is therefore expected to slow case disposal. However, Tamil Nadu, Pondicherry, and Andhra Pradesh had already removed all time limits on judgment delivery as early as 1930. For these states, the 2002 Act effectively reintroduced binding deadlines, tightening procedures relative to their pre-reform status. Accordingly, Chemin assigns these states a net score of $+1$ for this provision (a baseline -1 offset by a $+2$ adjustment), reflecting an improvement in judicial speed.

Applying this logic across all speed-relevant provisions, Chemin computes a state-specific total impact score for the 2002 Amendment Act, which summarizes the cumulative procedural change induced by the reform in each state.[17] These scores range from 34 to 40 across states.[18] I use this total impact score as a treatment-intensity index, capturing the extent to which each state was newly exposed to the 2002 reform. This treatment index is interacted with post-reform indicators in a difference-in-differences framework to identify the causal effect of improvements in judicial speed on occupational choices.

[17]The states of Jammu and Kashmir and Nagaland are excluded, as the Code of Civil Procedure was not applicable in these states.

[18]Chemin (2012) provides a detailed illustration of how Uttar Pradesh receives a score of 34, accounting for its full history of prior amendments (see Table A1, p. 484).

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