How Does Caste Affect Entrepreneurship? Birth versus Worth

Sampreet Goraya*

First Version: July 2019. This Version: April 2022

Abstract

I investigate the relative importance of the caste system in explaining resource misallocation in India and quantify its impact on aggregate productivity. I document three main stylized facts. First, firms of historically disadvantaged castes have a higher average revenue product of capital, $arpk$, relative to firms owned by high castes. Second, cross-caste differences in $arpk$ are primarily driven by small firms. Third, the majority of these differences are concentrated in financially underdeveloped regions in India. In a quantitative model of entrepreneurship, I find that the majority of cross-caste differences in $arpk$ are explained by differences in access to credit and that such asymmetries reduce total factor productivity by 3.6% and output per worker by 6.6% in the entrepreneurial sector.

Keywords: Misallocation, Caste System, Credit Constraints, Entrepreneurship

JEL Codes: O11 E44 D24 D61

*Department of Economics, Stockholm School of Economics. Email: sampreet.goraya@hhs.se. I am grateful to Julian di Giovanni, Manuel Garcia Santana, and Alessandro Tarozzi for their invaluable support. I also thank Andrea Caggese, Joseph Kaboski, Christian Fons-Rosen, Benjamin Moll, David McKenzie, Edouard Schaal, and Christopher Woodruff, as well as participants of CREI international lunch, 2nd CESC conference, V winter workshop MOVE/UAB, NEUDC Dartmouth 2020, PEDL conference 2020, Royal Economic Society conference 2021, MWIEDC Northwestern 2021, EUDN 2021, ASWEDE 2021, ACEGD 2021, and World Bank ETIFE for helpful discussions and comments. I would like to thank Lakshmi Iyer for generously sharing state-level aggregates of the Economic Census.

1 Introduction

A large body of literature has argued that the misallocation of resources explains a substantial fraction of cross-country differences in aggregate productivity.[1] A number of market-oriented distortions, such as financial frictions, labor market regulations, and size-dependent policies, among others, have been proposed as being responsible for resource misallocation. However, we lack systematic evidence about the quantitative importance of informal institutions in generating aggregate misallocation.

This paper quantifies the effects of one such institution – the caste system in India – on aggregate productivity. In particular, I explore the hypothesis that "birth and not worth" – that is, the caste instead of the productivity of individuals – determines the way in which resources are allocated in the economy. Historically, the caste system sorted people into different occupations and restrained any mobility, suppressing the entrepreneurial prowess of a vast section of society. While mobility restrictions for dominant castes have weakened over time, the caste system remains a salient feature of India.[2]

I use firm-level data to provide evidence that is consistent with the presence of high levels of *caste-driven* resource misallocation. My empirical analysis exploits data from the Micro, Small and Medium Enterprises (MSME) survey of 2006-2007. This dataset provides a representative sample of MSMEs together with an exhaustive list of balance sheet variables and information on the caste of the enterprise owner and employees, a feature missing in other commonly used firm-level datasets in India.[3] Using this dataset, I establish three main stylized facts.

First, on average within a sector, low-caste (LC) and middle-caste (MC) entrepreneurs

[1] See Banerjee and Duflo 2005, Restuccia and Rogerson 2008, Guner, Ventura, and Xu 2008, De Mel, McKenzie, and Woodruff (2008), and Hsieh and Klenow 2009. See Hall and Jones (1999) and Caselli and Feyrer (2007) for cross-country productivity differences.

[2] See Munshi (2016). Traditionally, entrepreneurship and financial intermediation belonged to one group called "Vaishyas"; however, these occupations have spilled over to other high castes such as "Brahmins" and "Kshatriyas"; see Damodaran (2008). The high castes represent 31.2% of the population, whereas low and middle castes represent 29.5% and 39.3% of the population, respectively.

[3] The most commonly used datasets are the Annual Survey of Industries and Prowess. They do not include the caste of the enterprise owner.

have 25%-30% and 13%-22% higher average revenue product of capital ($arpk$), respectively, relative to high-caste (HC) entrepreneurs with similar characteristics. Furthermore, non-HC entrepreneurs are also characterized by lower credit-to-capital and credit-to-output ratios relative to HC entrepreneurs. Second, I find that most of the cross-caste *dispersion* in $arpk$ is driven by small entrepreneurs. In particular, moving from the smallest to the largest entrepreneur in the economy, $arpk$ for LC entrepreneurs declines from being 52% higher than that of HC firms to approximately 12%.

Third, cross-caste $arpk$ differences negatively correlate with regional financial development. In particular, I construct a credit-to-output ratio for each state and use it as a measure of financial development. The observed differences in $arpk$ across castes fall as the credit-output ratio increases. I observe that LC firms have an $arpk$ that is double the value of HC firms in the states with the lowest financial development, such as Bihar, Jharkhand, and Uttar Pradesh, whereas no such differences are observed in states with well-functioning financial markets.

To rationalize these facts, I build a quantitative model of entrepreneurship in the spirit of Lucas Jr (1978), Quadrini (2000), and Buera, Kaboski, and Shin (2011). The model has two sectors of production: the corporate sector and the noncorporate sector (also called the entrepreneurial sector), and both produce a single good. The corporate sector constitutes a representative firm, whereas the noncorporate sector is populated by entrepreneurs.

The households from different castes can choose to become either entrepreneurs or workers in the context of *caste-dependent access to credit*. Moreover, the model allows for intertemporal savings to capture the self-financing channel, as in Banerjee and Moll (2010), Midrigan and Xu (2014), and Moll (2014).[4] The quantitative predictions crucially depend on the identification of three parameters that govern the degree of financial frictions in the economy. I use caste-specific credit-to-output ratios to calibrate these parameters.

[4]See also Gopinath, Kalemli-Özcan, Karabarbounis, and Villegas-Sanchez (2017) and Buera and Shin (2013).

The model finds substantial differences in access to credit across castes. In the benchmark calibration, the model identifies the degree of financial frictions as 53% and 47% more stringent for LC and MC entrepreneurs, respectively, relative to those of HC entrepreneurs. Furthermore, the model can explain the majority of the value computed in the data for the cross-caste differences in $arpk$. In particular, the $arpk$ of LC and MC entrepreneurs is 24.0% and 21.6% higher, respectively, than that of HC entrepreneurs. Such cross-caste asymmetries in borrowing constraints not only reduce the borrowing capacity of incumbents but also hinder the entry of productive but poor non-HC entrepreneurs. As a result, the model estimates an enterprise share of 24.6% for low castes (relative to 16% in the data), whereas its population share is 29.5%.

In line with the data, the model also predicts lower household income and wealth for non-HC households relative to HC households. Moreover, the model also predicts more concentration of wealth and income among HC households relative to non-HC households. The difference is a result of the lower wealth creation among the entrepreneurs of non-HC households as they face strict borrowing constraints. Therefore, to a certain extent, the model also rationalizes the persistent cross-caste disparities in wealth and income.

Finally, I model regional financial development as a shock to credit supply that affects all castes proportionately. I consider each region as a separate general equilibrium economy and compare the steady-state levels of $arpk$ differences across castes. The model predicts a declining cross-caste $arpk$ difference with regional financial development, as it particularly benefits relatively more constrained entrepreneurs, who are concentrated among non-HC castes.

In what follows, I use the model to conduct various counterfactual exercises. First, I allow non-HC entrepreneurs to have a borrowing capacity that is similar to their HC counterparts. The model identifies gains of 3.6% in aggregate TFP and 6.6% in output per worker in the entrepreneurial sector. Further, I use the model to decompose TFP gains at the extensive and intensive margins. First, the reallocation of capital from unproductive HC entrepreneurs to more productive non-HC entrepreneurs increases the

allocative efficiency of the economy; therefore, as a result, cross-caste $arpk$ differences fall to nil, and the overall dispersion in $arpk$ declines by 26%. These changes result in a 2.26% rise in TFP. Second, the reduction in borrowing constraints induces the entry of more non-HC entrepreneurs. The share of LC enterprises increases from 24.6% in the benchmark economy to 29.5%. Moreover, the excess entry of entrepreneurs increases demand for capital and labor. This implies an increase in the interest rate by approximately 0.54 percentage points, which further leads to the exit of unproductive but wealthy HC entrepreneurs, and this improvement in selection further increases TFP by 1.34%. In light of these results, I conclude that these caste-specific asymmetries in the financial markets are an important source of misallocation in India as highlighted in Hsieh and Klenow (2009).

Literature review: This paper contributes to the literature on race and ethnicity-based distortions, and misallocation. Hsieh, Hurst, Jones, and Klenow (2019), and Cassan, Keniston, and Kleineberg (2021) focus on the allocation of talent across occupations.[5] Hjort (2014) shows that inter-ethnic rivalries generate misallocation. Banerjee and Munshi (2004) document the misallocation of capital across communities in Tirupur (India). This paper quantifies the *aggregate* effects of caste-specific misallocation.

This paper also builds on the work of Thorat and Sadana (2009), Iyer, Khanna, and Varshney (2013), Deshpande and Sharma (2013), and Jodhka (2010), who document substantial caste differences in entrepreneurship rates, employment, and growth rates in India. Fisman, Paravisini, and Vig (2017) *provide evidence on the importance of caste match between lender and borrower for the access to credit*.[6] This paper formalizes the idea of caste-specific borrowing limits.

This paper is related to the papers that link finance, wealth, and entrepreneurship, such as Quadrini (2000) and Cagetti and De Nardi (2006), among others. This pa-

[5] See Erosa, Fuster, Kambourov, and Rogerson (2017), and Morazzoni and Sy (2021) for misallocation across gender in the US.

[6] They find that a lender of a certain caste increases credit access and reduces collateral requirements for a borrower of the same caste. In general, it is more likely that an owner of a bank, a bank manager, or a loan officer is an HC individual.

per quantifies the effects of caste-dependent financial frictions on entrepreneurship, wealth and income inequality.

My methodology can be used to quantify the effects of discrimination arising from various other informal institutions and norms. In this sense, this paper also links to a broader literature regarding the economics of discrimination,; see, for instance, Becker (1957), Phelps (1972), Arrow (1973), and Akerlof (1976).

The remainder of the paper is organized as follows. Section 2 describes the institutional setup, and Section 3 describes the data. Section 4 documents stylized facts. Section 5 presents the theoretical framework. Section 6 presents the main results, and Section **??** provides robustness exercises. Section 7 concludes.

The remainder of the paper is organized as follows. Section 2 describes the institutional setup, and Section 3 describes the data. Section 4 documents stylized facts. Section 5 presents the theoretical framework, and Section 6 presents the main results. Section 7 concludes.

2 Institutional Setup: The Caste System

The caste system is a form of social stratification that divides people into rigid hierarchical groups based on their occupation. For centuries, caste dictated customary social interaction, exclusion, and endogamy. In order of hierarchy, these groups are the Brahmins (priests and teachers), Kshatriyas (rulers and soldiers), Vaishyas (merchants and traders), and the Sudras (laborers and artisans). Further, there are two additional groups that fall outside the caste system. The first one embodies the group of people traditionally known as Dalits.[7] The second group of people is known as Scheduled Tribes. They have been subject to various forms of discrimination including *barriers to access capital and firm creation*. For the remainder of the paper, I ignore the micro structure of the caste system and primarily focus on a very broad definition. That is, low-caste individuals are denoted by "LC," which includes the Scheduled Castes and

[7] In the Indian constitution, Dalits have fallen under the category of Scheduled Castes since 1947. Scheduled Castes is an officially designated group of historically disadvantaged people.

Scheduled Tribes. Middle-caste individuals are denoted by "MC," which includes the Sudras (also known as Other Backward Castes, OBC, which fall between the traditional upper castes and the lowest castes). The high caste, denoted by "HC," includes the rest. The castes differ in many dimensions; however, I focus on one particular margin: access to credit markets.

3 Description of the Data

My main data source is the Micro, Small and Medium Enterprises (MSME) data from 2006 to 2007 (MSME 2009), the details of which are provided below. The details for other supplementary datasets are in Appendix A.[8]

MSME Dataset: The MSME dataset contains a representative sample of the *MSME sector* that comprises firms that invest less than INR 100 million (manufacturing firms) and INR 50 million (service firms).[9] The MSME dataset consists of two parts: a census of registered MSMEs and a sample survey of unregistered MSMEs (see Appendix A.1 for more details). A total number of 126,169 enterprises are surveyed to capture a representative sample of unregistered MSMEs. There are 1.65 million observations in total, of which 179,041 do not provide information on the wage bill. Therefore, I am left with 1.45 million observations (1.12 million in the manufacturing sector) after the cleaning process, which is described in detail in Appendix A.1. The descriptive statistics for manufacturing are provided in Table 1. As shown in Panel A.1, HC, MC, and LC represent 51%, 39.1%, and 9.8% of observations in the sample. In terms of total output, HC, MC, and LC firms produce 61.2%, 30.7% and 8%, respectively, whereas in terms of total credit, 75.1% is allocated to HC firms and only 4.7% to LC firms.

[8] I also compute various statistics with the Economic Census of India (EC) 2005, Indian Human Development Survey 2005 (Desai, Vanneman, and National Council of Applied Economic Research 2018), the Annual Survey of Industries (ASI) 2006, and the National Sample Survey (NSS) 2005-2006 (used in Hsieh and Klenow (2009)). The main advantage of using the MSME and EC is that they provide the caste of the enterprise owner together with other financial variables. However, MSME is not commonly used as the ASI-NSS or the CMIE Prowess (used in De Loecker et al. (2016)) because it omits large firms (above a certain threshold of capital stock) and does not have a panel dimension either.

[9] The MSME sector is estimated to employ about 59 million individuals in over 26.1 million units throughout the country. Further, 1.5 million (5.94%) are registered MSMEs and 24.5 million (94.06 %) are unregistered MSMEs. The registration is under the Factories Act of 1948 (See Appendix A.1 for more details).

Further, I provide firm-level statistics in Panel A.2 of Table 1. LC and MC firms are smaller and have lower leverage (defined as the ratio of credit to capital stock) than HC firms. Next, I exploit the retrospective information on output that is provided in the dataset. The average growth rate of output is around 9% and does not vary a lot across castes, whereas the dispersion in output growth is higher for HC firms relative to LC and MC firms. Further, I compute the default rates for each caste. Around 14.5% of LC firms defaulted in the last 12 months relative to 13.6% in the case of HC firms.[10]

Moreover, I compare the coverage of MSME data with other representative firm-level datasets, such as the Economic Census 2005 and the ASI-NSS 2005-2006. In the Economic Census 2005, firm ownership across castes is similar to the MSME dataset (see Panel B of Table 1).[11] Using the MSME threshold, I find that MSME firms in the ASI-NSS dataset represent 37% of the total output and 70% of output in the noncorporate sector (see Panel C in Table 1). The noncorporate sector includes proprietary or Hindu joint family firms, partnership firms, private limited companies, khadi, and village industries and handlooms, and the rest is placed under the corporate sector. In terms of firm-level characteristics, the average number of employees for MSMEs in the ASI-NSS dataset is 3.0.[12]

4 Emipircal Analysis

This section illustrates the observed differences in the average product of capital, $arpk$, and the average product of labor, $arpl$, across castes.

[10] These numbers suggest that, at least among MSMEs, riskiness may not be the primary driver of low credit allocation to LC entrepreneurs.

[11] In this dataset, I cannot separate out the MSMEs as there is no information on the capital stock; therefore, I report results for the whole manufacturing sector.

[12] According to the reports generated by the Ministry of Micro, Small and Medium Enterprises in India, the threshold for a firm to be defined as MSME is in "cumulative investment in plant and machinery (original cost)" (see Garcia-Santana and Pijoan-Mas 2014 for more details). This variable is available in the ASI-NSS dataset as the *value of plant and machinery owned by the firm*.

Fact 1: *arpk* is high for LC and MC firms.

For firm i in sector s with owner of caste c, $arpk_{isc} := \ln(ARPK_{isc}) = \ln(Y_{isc}) - \ln(K_{isc})$ and $arpl_{isc} := \ln(ARPL_{isc}) = \ln(Y_{isc}) - \ln(L_{isc})$. The variable Y_{isc} is gross value added, K_{isc} is capital, and L_{isc} is labor input, measured as the wage bill (see Hsieh and Klenow 2009). To evaluate *arpk* differences and to control for sector and regional heterogeneity, I run the regression

$$ln\, Y_i = \beta_0 + \beta_1 \mathbf{1}_{L-CASTE} + \beta_2 \mathbf{1}_{M-CASTE} + \sigma' \Gamma + \epsilon_i. \tag{1}$$

The dependent variables are $\{arpk, arpl\}$. The explanatory variables are the dummies for low castes, $\mathbf{1}_{L-CASTE}$, and the middle castes, $\mathbf{1}_{M-CASTE}$, whose corresponding coefficients are β_1 and β_2. The estimators $\widehat{\beta_1}$ and $\widehat{\beta_2}$ are interpreted as the percentage difference in the dependent variable between low- and high-caste firms and the middle- and high-caste establishments, respectively. The regressions include four-digit sector and district fixed effects.[13]

The estimates document that MC and LC firms have 13% and 25% higher *arpk*, whereas *arpl* is 5% higher for MC firms and no significant differences for LC firms are observed relative to HC firms, respectively (see Table 3). Further, the regression estimates with sampling weights find that MC and LC firms have 22% and 30% higher *arpk* relative to HC firms (refer to Table B.5 in Appendix B.1). Further, I provide robustness checks by including control variables that may be correlated with caste. Here, I include firm-level wages and mean schooling rates, land holdings, and dispersion in output growth that are computed at the sector-state-caste level. The *arpk* differences across castes remain high (see Table B.6 in Appendix B.1).

In order to compare the cross-caste *arpk* differences for different sectors, I compute *arpk* differences in the top twenty-five 3-digit sectors in terms of low castes' output share. In the sectors, where LC output share is largest, their *arpk* is also substantially

[13] Additionally, there is a vector of controls, Γ, that includes gender of the owner and religion fixed effects.

higher relative to HC (55% on average). The top 25 sectors (in terms of LC output) constitute up to 88% of the total LC output among MSMEs. These sectors constitute up to 87% of the total output among MSMEs. Moreover, these sectors constitute up to 60% of the national manufacturing output (see Table B.4 in Appendix B).

Finally, given the fact that cross-caste differences in $arpk$ are much larger and more robust across various specifications compared with $arpl$, from here onward, I will primarily focus on the observed differences in $arpk$ and explore its various facets.[14]

Fact 2: ARPK differences across castes decline with size.

Here, I document the evolution of $arpk$ differences over firm size. I divide enterprises into five different size bins, defined by output, and compute β_1 and β_2 for each size bin using the regression model described in equation 1. As shown in Figure 1a, large $arpk$ differences persist among smaller enterprises, but these differences are significantly small for large firms. In fact, the $arpk$ is highest for LC firms in the lowest decile of the size distribution, +52% relative to that of HC firms, and it declines by 40 percentage points (p.p.) and stands at +12% for firms in the top decile of the size distribution. A similar decline is observed for MC firms as well (see Figure 1b). In this case, the $arpk$ differences between MC and HC firms decline by 14 p.p.[15] To a certain extent, these results are consistent with the existing evidence on financial frictions and firm size (see, Hadlock and Pierce 2010), which suggests that small entrepreneurs are relatively more constrained. These results will also motivate the presence of the size-dependent borrowing capacity of entrepreneurs in the quantitative analysis.

[14] Oh (2019) shows how caste affects labor supply in India. However, its inquiry is left for future projects.

[15] A similar but less steep convergence is also documented over firm age; however, in this case, substantial $arpk$ differences remain even for older firms in the sample. For instance, the $arpk$ is highest for young LC entrepreneurs, +26% relative to that of HC establishments, and it declines by 4 p.p. over age (see Appendix B for details).

Fact 3: ARPK differences decline with financial development.

In this section, I provide evidence on how regional financial development changes cross-caste dispersion in $arpk$, the capital-labor ratio, and profitability. Ayyagari et al. (2014) document large and persistent differences in financial development across states in India. I construct a credit-to-output ratio for each state and use it as a measure of financial development.[16] I use a regression model to pin down the elasticity of $\{arpk, k/l, profits\}$ to financial development for LC and MC entrepreneurs. I interact the caste dummies with the financial development of states Fd_s. The regression specification is

$$\begin{aligned} ln\, Y_i = &\hat{\gamma}_0 + \hat{\gamma}_1 \mathbf{1}_{L-CASTE} + \hat{\gamma}_2 \mathbf{1}_{L-CASTE} \times Fd_s + \hat{\gamma}_3 \mathbf{1}_{M-CASTE} + \\ &\hat{\gamma}_4 \mathbf{1}_{M-CASTE} \times Fd_s + \hat{\gamma}_5 Fd_s + \Gamma + \epsilon_i, \end{aligned} \tag{2}$$

where $\hat{\gamma}_2$ and $\hat{\gamma}_4$ represent the elasticity of the dependent variable to Fd_S for LC and MC entrepreneurs, respectively, with respect to HC entrepreneurs. The value of $\hat{\gamma}_2$ and $\hat{\gamma}_4$ is significantly negative for $arpk$, suggesting an improved allocation of capital across castes in regions with high financial development (see Table 4). Further, I find that LC and MC entrepreneurs, who are less capital intensive relative to HC entrepreneurs on average, increase their capital-labor ratio with regional financial development.

Finally, I analyze how better financial conditions affect firm profitability.[17] In principle, low financial constraints lead to more entry of firms at the margin (see, e.g., Cagetti and De Nardi 2006, which analyzes the role of borrowing constraints as determinants of entrepreneurial decisions). This implies that as LC firms are able to access easy credit, one should expect more entry of firms and lower profitability on average as the productivity threshold to become an entrepreneur decreases. In the data, I find that LC and MC firms are more profitable than HC firms on average; however, these

[16] State-wise indicators on GDP and domestic credit are taken from the RBI's Handbook of Statistics on Indian states.

[17] The profitability is $\frac{Y-wL-RK}{Y}$, where Y is value added, wL is the wage bill, and RK is the cost of capital, respectively.

differences decline as the regional financial condition improves (see Table 4).

In this section, I have documented three stylized facts that suggest the misallocation of capital across castes. However, the welfare implications of these facts are not straightforward and depend on various general equilibrium forces. In the next section, I describe a quantitative model that is used to understand the macroeconomic implications of caste-specific distortions in the capital markets.

5 Theoretical Framework

The model is an extension of the frameworks used in Buera and Shin (2013) and Quadrini (2000). Time is discrete, and there is a measure M of infinitely lived agents that are heterogeneous across productivity z, assets a, and caste c. Every period, agents choose to become either workers or entrepreneurs based on their wealth a and entrepreneurial productivity z, and this occupational choice is represented by o_t. Financial wealth is determined endogenously, whereas productivity follows a stochastic process such that agents retain their last-period productivity z_t with probability ψ, and with probability $1-\psi$, they draw their new productivity from a Pareto distribution whose probability density is $\eta z^{-(\eta+1)}$ for $z \geq 1$. The parameter ψ represents the persistence, whereas η captures the dispersion in the productivity process. The households' caste remains constant over time. There are three sectors: the household sector, the production sector, and the intermediation sector. I start with the description of the household sector.

5.1 Households

Preferences: Agents' utility functions are strictly increasing and concave and satisfy standard Inada conditions. Agents discount their future utility at a discount rate ρ, and at any point in time t, their preferences are represented by the function

$$\mathbb{E}\sum_{t=o}^{\infty}\rho^t\frac{\mathcal{C}_t^{1-\gamma}-1}{1-\gamma}.$$

5.2 Production Sector

There are two sectors of production: the noncorporate sector and the corporate sector. These two sectors differ in terms of technology employed to produce a single homogeneous good that is used for both consumption and investment. The output price is normalized to one. The differentiation between these sectors tries to capture the nature of firms. The noncorporate sector is populated by entrepreneurs that will operate small and risky firms, whereas the corporate sector represents large conglomerates (e.g., firms listed on the stock market).

Corporate Sector: Following Quadrini (2000), the corporate sector has a representative firm that uses constant returns to scale production technology, given by

$$Y_c = F(K_c, N_c) = K^{\theta_c} N^{1-\theta_c},$$

where Y_c is output produced, K_c is the input of capital hired, and N_c is the amount of labor hired. The capital depreciates at the rate δ.

Noncorporate Sector: The noncorporate sector is populated by households that choose to become entrepreneurs. These entrepreneurs have access to a decreasing returns to scale production function $f(z,k,l) = z\,(k^{\alpha} l^{\beta})^{1-\nu}$, where $\alpha + \beta = 1$ and $1 - \nu$ is the span-of-control parameter that varies between 0 and 1. An entrepreneur rents capital k in the financial market and hires labor l to produce y units of a single good. Also, entrepreneurs need to pay a per-period fixed cost of operation κ.

5.3 Financial Markets

There is an intermediary that receives deposits from savers and lends these funds to entrepreneurs and the corporate sector. The lending activity is based on a constant returns to scale technology with a proportional cost per unit of funds intermediated. While this cost is zero for the corporate sector, the lending to entrepreneurs implies a proportional cost d. The cost of capital for entrepreneurs is $r_t + \delta + d$ in period t, where δ is a time-invariant depreciation cost and r_t is the deposit rate, and the cost of

capital for the corporate sector is $r_t + \delta$. The corporate sector is unconstrained in its ability to borrow. However, these entrepreneurs face borrowing constraints that take the following form:[18]

$$(1 + r_t + \delta + d)k_t \leqslant \phi\, \lambda_c\, a_t; \quad a_t \geqslant 0,$$

where $\phi \in [\underline{\phi}, \overline{\phi}]$ is a common component and $\lambda_c \in [1, \infty)$ is caste-specific component of the degree of credit constraints for entrepreneurs. The ϕ can be interpreted as a common shock to the credit environment that affects all castes proportionally. For a given ϕ, a large value of λ_c implies a high ability of entrepreneurs to borrow and low financial constraints.[19] I normalize $\phi = 1$ in the benchmark economy.

5.4 Recursive Formulation of Individuals' Problem

Agents maximize their expected utility for a given set of factor prices $\{w, r\}$, their asset base a, productivity z, and a vector of probabilities corresponding to future productivity z' given by $d\Upsilon(z'|c)$, such that the resource constraint always binds. The value function that agents maximize is

$$V(a, z, c) = \max\{V^w(a, z, c), V^e(a, z, c)\}. \tag{3}$$

The workers' value function is given by

$$\begin{aligned} V^w(a, z, c) = \max_{\mathcal{C}, a' \geqslant 0} u(\mathcal{C}) + \rho\{\psi V(a', z, c) + (1 - \psi) \int_{z'} V(a', z', c) d\Upsilon(z'|c)\} \\ \text{s.t.} \quad \mathcal{C} + a' \leqslant w + (1 + r)a. \end{aligned} \tag{4}$$

The entrepreneurs' value function is given by

[18] Collateral-based financial constraints are more common in India as the majority of loans are based on collateral and not on cash flows. For example, in 2014, majority of the loans required collateral in India according to the World Enterprise Survey 2014.

[19] Similar to Buera and Shin (2013), I rule out any borrowing for intertemporal consumption smoothing by assuming $a_t \geqslant 0$. This constraint is binding for workers, whereas it does not matter for entrepreneurs as they need to have a sufficiently large asset base to fund their capital requirements.

$$
\begin{aligned}
V^e(a,z,c) = \max_{\mathcal{C},k,l,a' \geqslant 0} & \; u(\mathcal{C}) + \rho\{\psi V(a',z,c) + (1-\psi)\int_{z'} V(a',z',c)d\Upsilon(z'|c)\} \\
\text{s.t.} \quad & \mathcal{C} + a' \leqslant z\,(k^{\alpha}l^{\beta})^{1-\nu_c} - wl - (r+\delta+d)k - \kappa + (1+r)a \\
& (1+r+\delta+d)k \leqslant \phi\,\lambda_c\,a.
\end{aligned} \tag{5}
$$

5.5 Recursive Competitive Equilibrium

Equilibrium: At time 0, given the distribution $\Lambda_0(a,z,c)$, the equilibrium of the economy is characterized by a sequence of allocations $\{o_t, \mathcal{C}_t, a_{t+1}, k_t, l_t, K_c, N_c\}_{t=0}^{\infty}$, factor prices $\{w_t, r_t\}_{t=0}^{\infty}$, and $\Lambda_t(a,z,c)_{t=1}^{\infty}$ such that

1. $\{o_t, \mathcal{C}_t, a_{t+1}, k_t, l_t\}_{t=0}^{\infty}$ solves the individuals' policy functions for given factor prices $\{w_t, r_t\}_{t=0}^{\infty}$.

2. The capital, labor, and goods markets clear in each period:

$$
\int_{o_t(a,z,c)=e} k_t\, d\Lambda_t(a,z,c) + K_c - \int a_t\, d\Lambda_t(a,z,c) = 0,
$$

$$
\int_{o_t(a,z,c)=e} l_t\, d\Lambda_t(a,z,c) + N_c - \int_{o_t(a,z,c)=w} d\Lambda_t(a,z,c) = 0,
$$

$$
\int_{o_t(a,z,c)=e} [z_t(k_t^{\alpha}l_t^{\beta})^{1-\nu_c} - \kappa] d\Lambda_t(a,z,c) + K_c^{\theta_c}N_c^{1-\theta_c} = \int \mathcal{C}_t d\Lambda_t(a,z,c) + (\delta+d)K + \delta K_c;
$$

3. The joint distribution of productivity, assets for each caste $\Lambda_t(a,z,c)_{t=1}^{\infty}$ evolve according to the equilibrium mapping

$$
\Lambda_{t+1}(a,z,c) = \psi \int_{\{z,a_{t+1}(a,z,c)<a\}} \Lambda_t(da,dz,c) + (1-\psi) \int_{\{z' \leqslant z, a'(a,z,c) \leqslant a\}} \Lambda_t(da,dz,c) d\Upsilon_t(z'|c).
$$

6 Quantitative Analysis

In this section, I evaluate the role of access to credit in explaining the cross-caste dispersion in the *arpk*. Further, I quantify the TFP losses due to resource misallocation generated by such asymmetries at the extensive and intensive margins. I begin by

calibrating the model to the manufacturing sector of India.[20] I then compare several nontargeted moments in the model and the data to validate the calibrated parameters.

6.1 Calibration

The calibrated parameters are provided in Table 5. The calibration strategy is based on Buera and Shin (2013) and Quadrini (2000). Overall, I need to specify values for 16 parameters: span-of-control of production technologies, dispersion and persistence in ability distributions, degree of financial frictions for each caste, fixed cost of operation, discount factor, coefficient of risk aversion, capital depreciation rate, and physical capital share in the corporate and noncorporate sectors, size of the corporate sector, intermediation cost, and population shares. The parameterization proceeds in two steps. First, I choose a set of parameters that are fixed outside the model.[21] Second, given the values of these fixed parameters, I choose the remaining parameters to match the salient features of the economy.

Fixed Parameters: A model period is one year. The annual depreciation rate for capital is $\delta = 0.06$, the capital income share in both sectors is $\alpha = \theta_c = 0.33$, and the coefficient of risk aversion is $\gamma = 1.5$, following Hsieh and Klenow (2009) and Cagetti and De Nardi (2006). The share of corporate sector capital in total capital is $\kappa_c = 0.68$. The population share for high castes is 31.2% , whereas that for low and middle castes is 29.5% and 39.3%, respectively, as computed in Indian Human Development Survey (IHDS) data.[22] Finally, the intermediation cost is fixed at $d = 0.033$ to match the net interest rate margin, as in Gu (2021).

Fitted Parameters: The remaining parameters are chosen in such a way that a number of statistics computed using a panel of simulated data are close to their empirical

[20] I choose the manufacturing sector for two reasons. First, because of restrictions on the data side, I can evaluate the proportion of output that is linked to MSMEs in the manufacturing sector but not in the service sector. This is important as I match this moment in the model to compute comparable statistics. Second; Hsieh and Klenow (2009) also evaluate the role of misallocation in the manufacturing sector in India, thus, focusing on the manufacturing sector helps me to gauge my results with respect to their findings.

[21] The fixed parameters are difficult to identify with the available data, so I use the values that are commonly used in the literature.

[22] I use the average between 2004 and 2012.

counterparts. The simulated data are drawn from the stationary distribution. The matched moments and their empirical counterparts are shown in Table 5.

Because of the non linearities involved, it is not possible to match particular parameters and moments. However, the mechanics of the model clearly indicate which are the key parameters for each set of moments. What follows is a summary description of the algorithm I used to select parameter values.

Column 6 of Table 5 shows the relevant moments in the Indian data. Further, Figure 3a shows the cumulative employment share distribution, and Figure 3b plots the cumulative distribution of income in the model and the data. In particular, I target the income share of the top 10%, 5%, and 1% of the population to capture the concentration of income at the top. Similarly, I target the top end of the employment share distribution to mimic the concentration of employment in the right tail.

The model targets an annual establishment exit rate of 8.8%.[23] The overall credit-to-output ratio is 0.44 (domestic credit to private sector as percentage of GDP, World Bank 2021). The credit-to-output ratio for LC and MC entrepreneurs relative to HC entrepreneurs is 0.53 and 0.48, respectively.

For some empirical moments such as the relative credit-to-output ratio for different castes as listed in Table 5, I use MSMEs. Therefore, I need to define MSME firms in the model as well. I evaluate MSME threshold $\bar{K}$ such that the total output produced by firms with a capital stock below $\bar{K}$ is matched with its data counterpart (see Section 3 for a discussion on the MSME capital threshold).

Column 5 of Table 5 shows the moments simulated from the calibrated model. All moments in the model are jointly determined by the fitted parameters. To a certain degree, however, they tend to be differentially linked to the parameters. For instance, the discount factor is set at $\rho = 0.92$ to match the annual interest rate of 5.7% and the capital-output ratio of 2.04.[24] The lower discount rate makes households less patient,

[23] Because of data access difficulties, I use the average exit rate for US manufacturing firms. The exit rates of firms in India and the US are not very different, as mentioned in Hsieh and Klenow (2014) on page 1043, paragraph 3. They compute the exit rate between 1992 to 1997 from the US Manufacturing Census and the exit rate between 1994-1995 to 2010-2011 from the Indian ASI-NSS.

[24] The annual real interest rate in India varies from 2% to 8.34% between 1999 and 2010. The capital-output ratio is taken from Feenstra et al. (2015).

which in turn decreases savings in the economy and raises the interest rate. The fixed cost of operation is set at $\kappa = 0.35$ to match the relative size of young firms with respect to all firms.[25] A higher fixed cost of operating means that relatively larger firms would enter the market, raising the size of young firms relative to incumbents.

I am thus left with six non standard parameters: $1-\nu, \eta, \psi, \lambda_{lc}, \lambda_{mc}, \lambda_{hc}$. Closely following Buera and Shin (2013), given the returns to scale, $1-\nu$, I choose the tail parameter of the entrepreneurial talent distribution, η, to match the right tail of the employment share distribution (or concentration at the top). This is done because, under a perfect credit benchmark ($\lambda \to \infty$), the employment distribution follows a Pareto distribution with a tail parameter proportional to the tail parameter of the entrepreneurial talent distribution.[26] I can then infer $1-\nu$ from the upper tail of the income distribution. The households at the top end of the distribution tend to be entrepreneurs in both the data and the model, and $1-\nu$ controls the share of output that goes to entrepreneurial input (see Figure 3a and Figure 3b). The persistence of the productivity process ψ is calibrated to match the annual exit rate of 8.8% in the model. The entrepreneurs in the model exit only if their newly drawn productivity is below the equilibrium cutoff level. A lower persistence implies higher churning of entrepreneurs in the model. The parameters related to financial frictions $\{\lambda_{lc}, \lambda_{mc}, \lambda_{hc}\}$ are fixed such that the overall credit-to-output ratio and the credit-to-output ratios for LC and MC entrepreneurs relative to HC entrepreneurs are also matched. A higher λ_c implies a larger supply of credit in the economy and hence higher leverage in the economy.

The calibration finds returns to scale equal to $1-\nu = 0.75$ and a scale parameter for productivity distribution $\eta = 4.80$. Further, the model identifies $\lambda_{lc} = 1.86$ and $\lambda_{mc} = 2.08$, which are significantly smaller than $\lambda_{hc} = 3.97$. This result is driven by the lower credit-to-output ratio of LC and MC entrepreneurs relative to that of HC entrepreneurs.

[25] I take the ratio of the average size of young firms (age between 0-4) and all firms from Akcigit, Alp, and Peters (2021).

[26] See Appendix C for a derivation of the employment distribution.

6.2 Wealth, Consumption, and Entrepreneurship

Here, I discuss the implications of financial frictions on individual decision making and how they differ across castes.

In the model, I imposed $a \geq 0$. This constraint is binding only for individuals who choose to be workers; it has no direct effect on the behavior of entrepreneurs for both castes, who need to hold assets for production because of the collateral constraint. A relatively higher degree of financial frictions for low castes distorts their occupational choice and makes them more likely to be workers than high castes. Therefore, average asset holdings are lower for LC households relative to HC households.

Further, in Figure 2, I highlight the differences in various policy functions of individuals in the model and discuss how they originate in the model. First, I compare consumption across individuals over the state space of assets. As expected, wealthier agents consume relatively more. However, when I compare high productivity individuals across castes, low castes consume less than the high castes, whereas no such difference appears among low productivity individuals. This result comes from the fact that high productivity individuals choose entrepreneurship, whereas low productivity individuals become workers. The workers are paid the same wage regardless of their caste, but entrepreneurial income depends on the ability of different castes to borrow from the financial markets. Low castes can borrow less relative to high castes, which in turn reduces their entrepreneurial output and income. A similar pattern is observed for asset growth rates across individuals of different castes (see Figure 2b). I will discuss the distributional impact of caste-specific borrowing constraints on income and wealth in Section 6.5.2.

6.2.1 Misallocation across Castes

The literature has stressed the role of financial frictions on two different margins of misallocation: the extensive margin and the intensive margin.

The intensive margin refers to the overall dispersion in $arpk$; however, this paper is primarily concerned with the $arpk$ dispersion across castes. The literature refers to

the dispersion in the marginal revenue product of capital ($mrpk$) as a misallocation of capital. The model implies that the $mrpk$ is directly proportional to the $arpk$, $mrpk = \alpha(1-\nu)arpk$, where $\alpha(1-\nu)$ is constant across caste. Therefore, dispersion in $mrpk$ directly translates into dispersion in $arpk$.

For constrained entrepreneurs, $mrpk$ is not equalize to the marginal cost and thus generates a wedge. This wedge decreases as the asset base of the entrepreneurs increases because it increases their borrowing capacity.

In Figure 2c, I plot the $arpk$ of high- and low-caste entrepreneurs with the same productivity and their difference over assets in the model. The $arpk$ is higher for low castes relative to high castes for every value of assets, and this difference stems from their lower ability to borrow, $\lambda_{lc} < \lambda_{hc}$. Further, the difference between the $arpk$ of low- and high-caste entrepreneurs declines with assets. On average, enterprises with a large asset base are large in size as well; therefore, a decline in the relative $arpk$ over assets in the model is in line with Fact 2 in Section 4.

The extensive margin refers to the distorted occupation choice. In particular, the occupation is determined by equation 3, and this decision is dynamic. In what follows, I present the occupational thresholds above which individuals choose to be entrepreneurs (see Figure 2d). The occupational threshold depends on two state variables; exogenous productivity z and endogenous assets a. In a world without financial frictions, the occupational choice is determined by productivity. Financial frictions affect the marginal entrants, as it deters the entry of poor but marginally productive individuals and promotes the entry of wealthy but marginally unproductive individuals. The stricter borrowing constraints for low castes exacerbate these forces and distort their occupational decision relatively more on the margin.

6.3 Nontargeted Moments

Here, we discuss the life-cycle implications of the model. Figure 3 compares the distributions produced by the model with a representative empirical distribution constructed using Indian data. I compare the employment share that belongs to different

cohorts. I divide the enterprises into different cohorts following Akcigit, Alp, and Peters (2021). Figure 3c reports the aggregate employment share by age for Indian manufacturing enterprises. In line with the literature, it is clear that the aggregate importance of old enterprises is small in India. While enterprises that are older than 25 years account for 55% of employment in the US, the corresponding number is less than 20% in India. Further, I compare the model with respect to the degree of selection. Figure 3d depicts the survival rate, the share of enterprises by age relative to the share of enterprises in the youngest age category. The rate of firm survival in the model is similar to that in the data.[27]

6.3.1 ARPK Dispersion across Castes

In a final validation exercise, I compare $arpk$ averages and their dynamics across castes. The model predicts that low and middle castes have 21.6% and 24.6% higher $arpk$ than high castes (see Panel A in Table 6). These values are in line with the empirical estimates, as reported in Column 3 of Table 6.

Moreover, in the spirit of Fact 2 in Section 4, I compare the $arpk$ estimates across small and large enterprises in the model with that in the data. The $arpk$ of low-caste enterprises drops from being 42% higher in the bottom decile to 10% (see Table 7) in the top decile of the size distribution relative to high castes. This finding is qualitatively similar to the findings in Fact 2 in Section 4.

In terms of the standard deviation $sd(arpk)$, the model under predicts the value (less than 50%) for each caste relative to the data (see Table 6). This could be because other forces – such as imperfect competition, heterogeneous input shares, measurement error, among others – may affect $sd(arpk)$ but are not present in the model.[28] In this way, one can interpret the $sd(arpk)$ predicted by the model as a fraction that can be explained by the financial frictions (together with perfect competition) in the context

[27] Because of data limitation, the distributions are constructed for all the firms in the data instead of the noncorporate sector, which generate bias.

[28] See Atkin, Khandelwal, and Osman (2019), Rotemberg and White (2021), and Bils, Klenow, and Ruane (2021).

of the Indian manufacturing sector.[29]

Further, the presence of heterogeneous borrowing constraints across castes also distorts their capital-labor ratio. Low castes experience a high shadow cost of capital that lowers their capital-labor ratio, as documented in Fact 3 in Section 4. Here, I compare those estimates with that of the model. The model predicts a 24.6% and 21.6% lower capital-labor ratio for low- and middle-caste enterprises relative to high castes. Finally, the model predicts that LC entrepreneurs are 11.7% and MC entrepreneurs are 10.4% more profitable than HC entrepreneurs, respectively, a finding that is in line with the data (see Table 6). Profitability is determined by a combination of forces. Stricter financial constraints increase the selection effect; however, they also limit the firm size and decrease profits. In the quantitative exercise, the selection effect dominates.

6.4 Quantitative Regional Analysis

In this section, I revisit Fact 3 in the spirit of the model. In the data, I find that the states that are more financially developed (i.e., those with a high credit-to-output ratio) have lower cross-caste dispersion in $arpk$. In order to assess the model's ability to capture this correlation, I vary the intermediation cost d and the common component of the financial constraints ϕ and report steady-state statistics.

We can view different values of credit supply shifter ϕ or intermediation cost d as representing different regions in India.[30] For instance, high ϕ or low d implies a region with developed financial markets. Table 7 reports the results. Region (ii) represents the benchmark economy. In region (iii), where intermediation cost is reduced to $d = 0$, I find an increase in the credit-output ratio and TFP. However, I find a slight increase in the $arpk$ difference across castes relative to the region (ii). The $arpk$ in absolute terms

[29] Further, the model predicts higher $sd(arpk)$ for LC entrepreneurs relative to HC entrepreneurs, whereas it is opposite in the data. This may be because of the differences in the underlying productivity process for each caste (e.g., Asker, Collard-Wexler, and De Loecker (2014) show that the underlying productivity process is an important driver of $sd(arpk)$. In this paper, I assume the productivity process to be the same across castes and focus solely on heterogeneous financial frictions. Allowing for heterogeneous productivity processes across castes may improve the model fit in this context.

[30] The approach of viewing different regions as different levels of credit supply shifter ϕ is more closely related to the exercise performed in Buera, Kaboski, and Shin (2011). I consider each region as a separate general equilibrium economy.

declines for all castes as the cost of capital is lower, but $arpk$ declines more so for HC entrepreneurs.

Further, in regions (iv) and (v), I increase credit supply shifter ϕ. The values of ϕ used in the simulation are able to generate variation in the credit-output ratio that is consistent with the data.[31] I find that it substantially increases the credit-output ratio and TFP and decreases cross-caste $arpk$ differences. This finding suggests a decline in the misallocation of resources, a result that is in line with Buera, Kaboski, and Shin (2011). These results are driven by the fact that large values of credit supply shifter ϕ push the majority of entrepreneurs out of credit constraints such that the credit supply shifter lowers the negative impact of caste differences in financial frictions λ_c. Therefore, it disproportionately benefits non-HC firms as they were relatively more credit constrained in the benchmark economy.

Finally, I compare these model predictions with data and find consistent results. In particular, Table 7 reports the cross-caste $arpk$ differences for regions with low (a), medium (b), and high (c) levels of financial development. Relative to HC entrepreneurs, the $arpk$ of LC entrepreneurs is 30% higher in less financially developed regions, whereas it is only 11.5% higher in regions with high financial development.

In the model, the differential impact of changes in ϕ and d on cross-caste $arpk$ differences may be driven by the fact that a decline in d directly increases entrepreneurs' borrowing capacity (equation 5.3) and decreases the cost of capital (consequently, increasing the desired level of capital), whereas an increase in ϕ increases entrepreneurs' borrowing capacity only in partial equilibrium. Therefore, the former is more potent in decreasing the gap between the actual and desired levels of capital.

6.5 Counterfactual Analysis

Here, I highlight the productivity and output gains from homogeneously allocating capital across castes. Therefore, in counterfactual analysis CF, I allow the degree of financial frictions for non-HC individuals to be similar to that of HC individuals (i.e.,

[31] The regional credit-output ratio varies between 0.10 to 1.91, whereas the ratio for the majority of regions is below 1.

$\lambda_{lc} = \lambda_{mc} = \lambda_{hc}$). The model predicts aggregate TFP gains of 3.6% in CF and output-per-worker gains of 6.6% (see Panel A in Table 8) in the noncorporate sector.[32]

These gains come from two main sources in the counterfactual economy. First, the reallocation of capital from unproductive HC entrepreneurs to more productive non-HC entrepreneurs increases the allocative efficiency of the economy. Therefore, as a result, the dispersion in $arpk$ declines by 26%. This decline in the dispersion in $arpk$ is driven by the decline in both within- and across-caste groups. In particular, the cross-caste dispersion in $arpk$ falls to zero as the average $arpk$ equalizes for HC and non-HC enterprises. For instance, the relative difference in average $arpk$ for low- and high-caste establishments falls from +24.6% in the benchmark economy to 0% in the counterfactual economy. As a result, the economy becomes more capital intensive, with gains of +9% in the aggregate capital-labor ratio. These gains come mostly from low- and middle-caste entrepreneurs, which increases their aggregate capital-labor ratio by 12% and 15%, respectively.

Second, the reduction in borrowing constraints induces the entry of more non-HC entrepreneurs at the margin (occupational choice, as shown in Figure 2d, becomes symmetrical across castes). The share of LC enterprises increases from 24.6% in the benchmark economy to 29.5% – that is, exactly proportional to their respective population weights. Moreover, because of the excess entry of entrepreneurs, demand for capital and labor increases. The interest rate increases by 0.5 p.p. and wages increase by 6.6%. This implies a higher cost of inputs of production in CF, which leads to the exit of unproductive HC enterprises.

Finally, I perform two more counterfactual exercises to highlight the importance of misallocation at the extensive and intensive margins and to disentangle the gains from these two sources. I start with the stationary distribution $\Lambda(z, a, c)$ and redistribute capital across entrepreneurs (equalizing λ_c), while the distribution of firms, total capital, and labor supply are the same. The reallocation of capital toward non-HC entrepreneurs increases TFP by 2.26%. This accounts for 62% of the total TFP gains.

[32] For the model, TFP is defined as $Y(K^{\alpha}L^{1-\alpha})^{-1}$, with $\alpha = 0.33$. Here, Y is aggregate output, K is aggregate capital, and L is employment.

Next, I allow the distribution $\Lambda(z, a, c)$ to adjust to changes in factor prices. This allows productive but poor non-HC entrepreneurs to enter the market and forces unproductive but wealthy entrepreneurs to exit the market. The TFP gains from removing talent misallocation at the extensive margin represent 38% of the total gains.

6.5.1 Firm Ownership Rates and Population Shares across Castes

In the data, low castes are 29.5%, middle castes are 39.3%, and high castes are 31.2% of the total population (see Table C.12 in Appendix C.1), whereas LC owns 16%, MC owns 47.5%, and HC owns 36.5% of total firms. In the benchmark model, LC owns 24.6%, MC owns 34.5%, and HC owns 40.8% of total firms (see Panel B in Table 6). In the counterfactual economy, where the degree of financial constraints are equalized, the enterprise ownership is equal to the population shares for each caste (as there are no other differences across castes).

The model predicts LC's enterprise share as equal to 24.6%, which is higher than what is observed in the data. This means that financial constraints can explain around one-third of the gap between the population share and enterprise share for low castes. Therefore, it seems that financial frictions are important but may not represent the whole story behind the caste differences in the enterprise share that are observed in the data. This hint toward potential heterogeneity in other factors such as fixed cost of operation that may be required to precisely match these shares in the model.

In order to assess these differences, I recalibrate the model with a heterogeneous fixed cost of production across castes together with heterogeneous borrowing constraints. I match the enterprise share for each caste to pin down these fixed costs. The model finds that the low castes face a much higher fixed cost of operation relative to high- and middle-caste entrepreneurs, whereas middle castes face a lower fixed cost of operation relative to high castes (see Table C.11 in Appendix C.1).[33] These differences may be driven by differences in factors such as production technology and barriers to firm creation.

[33]The fixed cost of operation for LC is ($\kappa_{lc} = 0.67$), HC is ($\kappa_{hc} = 0.40$), and MC is ($\kappa_{mc} = 0.30$).

In the counterfactual economy, where the degree of financial constraints is equalized, LC owns 22.2%, MC owns 45.7%, and HC owns 32.1% of total firms (see Table C.12 in Appendix C.1). Therefore, caste-specific borrowing constraints can explain around 6.2 p.p. of the difference between enterprise share and population share that is documented in the data for low castes. This result is similar to the findings in the benchmark model. The counterfactual TFP and output-per-worker gains are 3.1 and 6.1%, respectively, slightly lower than the gains in the benchmark model.

6.5.2 Wealth and Income Inequality across Castes

Hnatkovska, Lahiri, and Paul (2012) document that median (mean) LC households earns 21% (29%) less wages than non-LC households. Using All India Debt and Investment Survey, I report vast disparities in wealth holding across castes (see Table C.13).[34] Further, I document that wealth inequality is higher among HC households relative to non-HC households (see Table A.3 in Appendix A.5). Using IHDS data, I report that, on average, LC household income is half that of HC household income and income inequality is higher among HC households relative to non-HC households (see Table A.2 and Table C.13 in Appendices A and C).

In the benchmark calibration, for LC households, income is 6.0% and wealth is 16% lower relative to HC households on average.[35] The model produces results that are qualitatively similar in these two aspects; however, it substantially underestimates cross-caste inequality (see Table C.13 in Appendix C). This may suggest that caste-specific borrowing constraints do make low castes poorer on average but are not enough to match the cross-caste disparities in income and wealth as documented in the data.[36]

[34] See Bharti 2018 for more discussion on wealth inequality.

[35] Given that wages are the same across households in the model, the differences in the income distribution are driven by differences in profits and interest income on assets.

[36] To a certain extent, low cross-caste income inequality in the model is driven by equal wages for workers of all castes. If heterogeneous wages are introduced in the model for each caste (particularly, relatively low wages for non-HC workers), then one would expect higher enterprise ownership for non-HC households as the opportunity cost is lower relative to HC households. This would imply that even higher fixed costs (in a model with heterogeneous fixed costs) are required to match the enterprise ownership across castes relative to the benchmark economy. High fixed costs would increase both income and wealth inequality. Understanding the different determinants of cross-caste income and

Furthermore, income inequality is lower among LC households as 26% of their income is owned by the top 5% of households, whereas 28% of the total HC income is earned by the top 5% of HC households. Among the HC entrepreneurs, 48% of their wealth is owned by the richest 5%, whereas, among the LC entrepreneurs, 42% of their wealth is owned by the richest 5% of LC households (see Table C.14 in Appendix C.2).

In the counterfactual experiment, cross-caste wealth inequality declines as LC households become richer on average relative to the benchmark economy (wealth increases by 10.5% for LC households on average). Moreover, when LC firms are allowed to borrow more, wealth inequality within LC households increases as the upper tail of the distribution is able to create more wealth (see Table C.14 in Appendix C.2).

Cross-caste income inequality decreases as the average LC household is richer in the counterfactual economy (income increases by 7.4% for LC on average). Furthermore, I do not find significant changes in income inequality within LC households.

6.6 Comparison of Results with Existing Literature

Here, I focus on the quantitative results and discuss how they relate to the existing literature. Hsieh and Klenow (2009) argue that if capital and labor were efficiently allocated in India, then TFP would increase significantly. Therefore, through the lens of my model, I conclude that caste-specific asymmetries in the financial markets in India are important, and the removal of such obstacles could increase output per worker by 6.6% in the entrepreneurial sector. Further, in the case of financial frictions, Moll (2014) shows that the losses due to misallocation of capital depend on the persistence in the productivity process, ψ, and even small changes in ψ can lead to large differences in capital misallocation in the steady state. The estimates of persistence in this paper are in line with those found in Buera, Kaboski, and Shin (2011). Moreover, the estimated fixed cost of operation is much lower in my calibration than what is estimated in Buera, Kaboski, and Shin (2011). This factor may explain the bigger role for

wealth inequality is left for future research.

misallocation of capital in explaining productivity losses in this context.[37]

7 Conclusion

It is well established that the misallocation of resources can explain a large portion of productivity differences across countries. However, the sources of misallocation are still under investigation, and several firm-level distortions have been proposed. This paper suggests that the caste system in India is one example of such distortions and quantifies its importance in explaining aggregate TFP losses. I document that enterprises owned by historically disadvantaged castes exhibit a higher $arpk$, higher profitability, and a lower capital-labor ratio relative to high castes in India. I then use a quantitative model of entrepreneurship to understand the implications of cross-caste dispersion in $arpk$ on overall output and TFP. The model identifies a high degree of financial constraints for non-HC entrepreneurs and shows that such asymmetries reduce TFP by 3.6% in the entrepreneurial sector. Given the findings of this paper, a natural next step would be to understand the implications of the caste system on long-run growth.

References

Ufuk Akcigit, Harun Alp, and Michael Peters. Lack of selection and limits to delegation: firm dynamics in developing countries. *American Economic Review*, 111(1):231–75, 2021.

George Akerlof. The economics of caste and of the rat race and other woeful tales. *The Quarterly Journal of Economics*, pages 599–617, 1976.

Kenneth J Arrow. *The theory of discrimination*. Princeton University Press, 1973.

John Asker, Allan Collard-Wexler, and Jan De Loecker. Dynamic inputs and resource (mis) allocation. *Journal of Political Economy*, 122(5):1013–1063, 2014.

David Atkin, Amit K Khandelwal, and Adam Osman. Measuring productivity: Lessons from tailored surveys and productivity benchmarking. In *AEA Papers and Proceedings*, volume 109, pages 444–49, 2019.

Meghana Ayyagari, Asli Demirguc-Kunt, and Vojislav Maksimovic. Does local financial development matter for firm lifecycle in india? *The World Bank*, 2014.

Abhijit Banerjee and Kaivan Munshi. How efficiently is capital allocated? evidence from the knitted garment industry in tirupur. *The Review of Economic Studies*, 71(1):19–42, 2004.

[37] The sources of misallocation losses depend on the fixed cost of operation as mentioned in Buera, Kaboski, and Shin (2011), where sectors characterized by a low fixed cost tend to have major productivity losses due to misallocation of capital. Buera, Kaboski, and Shin (2011) find the per-period fixed cost of operation in manufacturing to be about three times the equilibrium wage in the perfect-credit benchmark, whereas this paper finds the per-period fixed costs of operation to be approximately half of the equilibrium wages.

Abhijit V Banerjee and Esther Duflo. Growth theory through the lens of development economics. *Handbook of Economic Growth*, 1:473–552, 2005.

Abhijit V Banerjee and Benjamin Moll. Why does misallocation persist? *American Economic Journal: Macroeconomics*, 2(1):189–206, 2010.

Gary S Becker. *The economics of discrimination*. University of Chicago press, 1957.

Nitin Kumar Bharti. Wealth inequality, class and caste in india, 1961-2012. *WID. world Working Paper*, 14, 2018.

Mark Bils, Peter J Klenow, and Cian Ruane. Misallocation or mismeasurement? Technical report, forthcoming Journal of Monetary Economics, 2021.

Francisco J. Buera and Yongseok Shin. Financial frictions and the persistence of history: A quantitative exploration. *Journal of Political Economy*, 121(2):221–272, 2013. ISSN 00223808, 1537534X. URL http://www.jstor.org/stable/10.1086/670271.

Francisco J Buera, Joseph P Kaboski, and Yongseok Shin. Finance and development: A tale of two sectors. *The American Economic Review*, 101(5):1964–2002, 2011.

Marco Cagetti and Mariacristina De Nardi. Entrepreneurship, frictions, and wealth. *Journal of Political Economy*, 114(5):835–870, 2006.

Francesco Caselli and James Feyrer. The marginal product of capital. *The Quarterly Journal of Economics*, 122(2):535–568, 2007.

Guilhem Cassan, Daniel Keniston, and Tatjana Kleineberg. A division of laborers: Identity and efficiency in india. Technical report, National Bureau of Economic Research, 2021.

Harish Damodaran. *India's new capitalists: caste, business, and industry in a modern nation*. Springer, 2008.

Jan De Loecker, Pinelopi K Goldberg, Amit K Khandelwal, and Nina Pavcnik. Prices, markups, and trade reform. *Econometrica*, 84(2):445–510, 2016.

Suresh De Mel, David McKenzie, and Christopher Woodruff. Returns to capital in microenterprises: evidence from a field experiment. *The Quarterly Journal of Economics*, 123(4):1329–1372, 2008.

Sonalde Desai, Reeve Vanneman, and New Delhi National Council of Applied Economic Research. *India Human Development Survey (IHDS), 2005*. Inter-university Consortium for Political and Social Research [distributor], 2018-08-08. https://doi.org/10.3886/ICPSR22626.v12, 2018.

Ashwini Deshpande and Smriti Sharma. Entrepreneurship or survival? caste and gender of small business in india. Technical report, Centre for Development Economics Department of Economics, Delhi School of Economics, 2013.

Andrés Erosa, Luisa Fuster, Gueorgui Kambourov, and Richard Rogerson. Hours, occupations, and gender differences in labor market outcomes. *NBER Working Paper*, (w23636), 2017.

Robert C Feenstra, Robert Inklaar, and Marcel P Timmer. The next generation of the penn world table. *American economic review*, 105(10):3150–82, 2015.

Raymond Fisman, Daniel Paravisini, and Vikrant Vig. Cultural proximity and loan outcomes. *American Economic Review*, 107(2):457–92, 2017.

Manuel Garcia-Santana and Josep Pijoan-Mas. The reservation laws in india and the misallocation of production factors. *Journal of Monetary Economics*, 66:193–209, 2014.

Gita Gopinath, Şebnem Kalemli-Özcan, Loukas Karabarbounis, and Carolina Villegas-Sanchez. Capital allocation and productivity in south europe. *The Quarterly Journal of Economics*, 132(4):1915–1967, 2017.

Jiajia Gu. Financial intermediation and occupational choice. *Journal of Economic Dynamics and Control*, 133:104238, 2021.

Nezih Guner, Gustavo Ventura, and Yi Xu. Macroeconomic implications of size-dependent policies. *Review of Economic Dynamics*, 11(4):721–744, 2008.

Charles J Hadlock and Joshua R Pierce. New evidence on measuring financial constraints: Moving beyond the kz index. *The Review of Financial Studies*, 23(5):1909–1940, 2010.

Robert E Hall and Charles I Jones. Why do some countries produce so much more output per worker than others? *The quarterly journal of economics*, 114(1):83–116, 1999.

Jonas Hjort. Ethnic divisions and production in firms. *The Quarterly Journal of Economics*, 129(4):1899–1946, 2014.

Viktoria Hnatkovska, Amartya Lahiri, and Sourabh Paul. Castes and labor mobility. *American Economic Journal: Applied Economics*, 4(2):274–307, 2012.

Chang-Tai Hsieh and Peter J. Klenow. Misallocation and manufacturing TFP in China and India. *The Quarterly Journal of Economics*, CXXIV(November), 2009.

Chang-Tai Hsieh and Peter J Klenow. The life cycle of plants in india and mexico. *The Quarterly Journal of Economics*, 129(3):1035–1084, 2014.

Chang-Tai Hsieh, Erik Hurst, Charles I Jones, and Peter J Klenow. The allocation of talent and us economic growth. *Econometrica*, 87(5):1439–1474, 2019.

Lakshmi Iyer, Tarun Khanna, and Ashutosh Varshney. Caste and entrepreneurship in india. *Economic and Political Weekly*, 48(6):52–60, 2013.

Surinder S Jodhka. Dalits in business: Self-employed scheduled castes in north-west india. *Economic and Political Weekly*, pages 41–48, 2010.

Robert E Lucas Jr. On the size distribution of business firms. *The Bell Journal of Economics*, pages 508–523, 1978.

Virgiliu Midrigan and Daniel Yi Xu. Finance and misallocation: Evidence from plant-level data. *The American Economic Review*, 104(2):422–458, 2014.

Benjamin Moll. Productivity losses from financial frictions: can self-financing undo capital misallocation? *American Economic Review*, 104(10):3186–3221, 2014.

Marta Morazzoni and Andrea Sy. Female entrepreneurship, financial frictions and capital misallocation in the us. 2021.

MSME. *Fourth All India Census of Micro, Small and Medium Enterprises, 2006*. Ministry of Micro, Small and Medium Enterprises, 2009. URL https://www.dcmsme.gov.in/ito_msme/censuses.htm.

Kaivan Munshi. Caste networks in the modern indian economy. In *Development in India*, pages 13–37. Springer, 2016.

Suanna Oh. Does identity affect labor supply. *Job Marker Paper, Columbia University*, 2019.

Edmund S Phelps. The statistical theory of discrimination. *American Economic Review*, 62(4):659–661, 1972.

Vincenzo Quadrini. Entrepreneurship, saving, and social mobility. *Review of economic dynamics*, 3(1): 1–40, 2000.

Diego Restuccia and Richard Rogerson. Policy distortions and aggregate productivity with heterogeneous establishments. *Review of Economic dynamics*, 11(4):707–720, 2008.

Martin Rotemberg and T Kirk White. Plant-to-table(s and figures): Processed manufacturing data and measured misallocation. In *Mimeo*, 2021.

Sukhadeo Thorat and Nidhi Sadana. Caste and ownership of private enterprises. *Economic and Political Weekly*, pages 13–16, 2009.

The World Bank. *Domestic credit to private sector by banks (percent of GDP)*. Indicator Code: FD.AST.PRVT.GD.ZS. Source: International Monetary Fund, International Financial Statistics and data files, and World Bank and OECD GDP estimates, 2021.

Tables and Figures

Table 1: Summary Statistics: Manufacturing Sector & Population Shares

	HC		MC		LC		Overall
	Total	%	Total	%	Total	%	Total
PANEL A.1: MSME 2006-2007 - Aggregate Statistics							
Observations (000s)	572	51%	438	39.1%	109	9.8%	1121
Establishments (000s)	2915	39%	3504	46%	1144	15%	7563
	Mean	%	Mean	%	Mean	%	Mean
Employment	3.41	46.7%	2.53	41.5%	2.18	11.7%	2.82
Output	285495	61.2%	119040	30.7%	95227	8.0%	179594
Capital	679811	70.3%	195465	24.3%	133282	5.4%	372573
Credit	27689	75.1%	6158	20.1%	4462	4.7%	14200

PANEL A.2: MSME 2006-2007- Firm-level Statistics

	HC	MC	LC	All
	Mean (S.D.)	Mean (S.D.)	Mean (S.D.)	Mean (S.D.)
Output/Capital (log ARPK)	-0.21 (1.36)	0.02 (1.22)	0.25 (1.22)	-0.03 (1.29)
Output/Labor (log ARPL)	0.63 (1.00)	0.60 (0.92)	0.88 (1.08)	0.66 (0.99)
Credit/capital	3.6%	1.6%	2.1%	2.4%
Credit/Output	8.4%	4.2%	2.6%	5.6%
Δ Output (Mean)	9.4% (0.29)	9.0% (0.23)	9.2% (0.25)	9.2% (0.26)
Default Rate	13.6%	13.1%	14.5%	13.8%

PANEL B: Economic Census 2005

	HC		MC		LC		Overall
	Total	%	Total	%	Total	%	
Establishments (000s)	2924	36.5%	3818	47.5%	1286	16%	8029
	Mean	%	Mean	%	Mean	%	
Employment	3.86	49%	2.39	39.6%	2.0	11.2%	2.9

PANEL C: ASI-NSS 2005-2006

	Overall		Noncorporate sector	
	Output	Labor	Output	Labor
Average (all)	437258	3.3	191864	2.9
Average (MSME)	161107	2.9	133048	2.8
Share of MSME in ASI-NSS	36.9%	89.8%	70%	97.3%

PANEL D: IHDS

	HC	MC	LC
Population Share	31.2%	39.3%	29.5%
Share of Entrepreneurs	5.5%	4.6%	2.3%

Notes: The table reports descriptive statistics. HC, MC, and LC represents the low-caste, middle-caste, and high-caste entrepreneurs, respectively.
Panel A.1 reports statistics for the MSME dataset. For each caste, the first column reports total number in case of Observations, and Establishments, and the mean value for Employment, Output, Capital and Credit. The second column reports respective caste shares in the overall dataset for each row. The Observations report the number of enterprises available in the sample. For Establishments, I compute total number of MSME enterprises by multiplying the observations with their respective sampling multiplier provided in the data. The employment is measured as number of employees (e.g., avergae number of employees for HC firms are 3.41 and HC firms employ 46.7% of overall workforce), and output, capital and credit is in Indian rupees. Sampling multipliers are applied.
Panel A.2 reports firm-level statistics for MSMEs. S.D. is standard deviation. The ARPK and ARPL are in logs. The credit-output and credit-capital ratios are reported for all firms (denoted as zero if no credit). Output is value-added and credit is the amount of outstanding loans. Sampling multipliers are applied.
Panel B provides summary statistics for manufacturing firms in the Economic Census 2005. Establishments reprsents total number of productive units for each caste in the data (and their share). Employment reports the mean value of number of employees for each caste (and the share of workforce employed by entrepreneurs of each caste).
Panel C provides statistics for the ASI-NSS 2005. The noncorporate sector includes privately owned and private limited enterprises, Khadi and village industries, and handlooms. Sampling multipliers are applied for MSME and ASI-NSS datasets. MSMEs in the ASI-NSS dataset are firms with Investment$<$ INR 100 million.
Panel D provides statistics for population shares as computed with IHDS data. I compute population shares as average between two datasets (IHDS 2004 and 2012). The Share of entrepreneurs is computed as the number of entrepreneurs (individuals who report business as their main activity) as the share of population (variable is available in IHDS 2012).

Table 2: Sectoral Shares across Castes

Sector	NIC	LC Share	MC Share	HC Share	Sector Share
Manufacture of food products and beverages	15	0.016	0.054	0.106	0.090
Manufacture of wearing apparel	18	0.013	0.049	0.052	0.035
Manufacture of tobacco products	17	0.009	0.040	0.079	0.081
Manufacture of furniture; manufacturing n.e.c.	36	0.008	0.035	0.036	0.036
Manufacture of fabricated metal products	28	0.006	0.027	0.057	0.038
Manufacture of wood and of products of wood	20	0.006	0.014	0.017	0.015
Manufacture of other non-metallic mineral products	26	0.003	0.017	0.043	0.051
Manufacture of machinery and equipment n.e.c.	29	0.003	0.014	0.044	0.057
Tanning and dressing of leather	19	0.002	0.003	0.008	0.008
Manufacture of rubber and plastics products	25	0.002	0.006	0.024	0.024
Manufacture of chemicals and chemical products	24	0.002	0.009	0.037	0.133
Manufacture of basic metals	27	0.002	0.006	0.028	0.113
Publishing, printing and reproduction of recorded media	22	0.002	0.008	0.014	0.017
Manufacture of tobacco products	16	0.001	0.004	0.007	0.020
Manufacture of electrical machinery and apparatus n.e.c.	31	0.001	0.007	0.017	0.035
Manufacture of radio, television and communication equipment	32	0.001	0.002	0.004	0.015
Manufacture of other transport equipment	35	0.001	0.003	0.011	0.025
Manufacture of medical, precision and optical instruments	33	0.001	0.003	0.007	0.008
Manufacture of paper and paper products	21	0.000	0.003	0.012	0.014
Manufacture of motor vehicles, trailers and semi-trailers	34	0.000	0.002	0.005	0.064
Manufacture of coke, refined petroleum products and nuclear fuel	23	0.000	0.001	0.002	0.115
Manufacture of office, accounting and computing machinery	30	0.000	0.000	0.002	0.007
Recycling	37	0.000	0.000	0.000	0.000
Total		0.080	0.307	0.613	1.000

Notes: The table presents weighted average ARPK (in logs), where weights are firm-level capital shares, in all the 2-digit sectors (in manufacturing). The table is sorted in terms of LC's output share (largest to smallest). The variables "LC share","MC share" and "HC share" contain output share of LC, MC, and HC firms in that sector, respectively (computed in MSME dataset). The "sector share" contains sectors' output share in the national manufacturing output (computed with ASI-NSS dataset). The total output share of MSMEs' in manufacturing is 38%. The weighted average ARPK (in logs) of HC, MC, and LC firms in the aggregate economy is -1.80, -1.28, and -1.24 and unweighted average ARPK of HC, MC, and LC firms is -0.21, 0.02 and 0.25, respectively. The Sampling multipliers are applied. The sector names are truncated for presentation purposes and to see the full name, refer to NIC 2004 classification.

Table 3: ARPK and ARPL across Castes

	(1) *arpk*	(2) *arpl*
M-caste	0.13***	-0.05***
	(0.02)	(0.00)
L-caste	0.25***	-0.02
	(0.02)	(0.35)
Constant	-0.67***	0.61***
	(0.01)	(0.01)
Obs.	1,121,610	1,084,632
R-squared	0.51	0.32
District FE	✓	✓
NIC4 FE	✓	✓

Notes: The table shows results from the enterprise level regression using equations 1 for manufacturing sector. Dependent variables are in logs and are shown in column headings. The variables *arpk* and *arpl* are the average products of capital and labor, respectively. M-caste is the dummy variable for the middle-caste enterprises. L-caste is the dummy variable for the low-caste enterprises. All specifications includes sector, district (586 in total), gender of the owner and religion fixed effects. Standard errors are in parentheses, clustered at the caste, state and sector level. To see the regression estimates with sampling weights, refer to Table B.5 in Appendix B. In that case, MC and LC firms have 21% and 30% higher *arpk* relative to HC firms. Further, differences in *arpl* are also larger but remain smaller than that of *arpk*. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Regional Financial Development and Capital Allocation

	ARPK	ARPK	K/L	K/L	Profit Rate	Profit Rate
M-caste	0.13***	1.28***	-0.26***	-1.28***	0.02**	0.70***
	(0.02)	(0.21)	(0.02)	(0.18)	(0.01)	(0.14)
L-caste	0.25***	1.32***	-0.49***	-1.43***	0.05***	0.68***
	(0.03)	(0.21)	(0.03)	(0.19)	(0.02)	(0.15)
FD		0.82***		-0.28		0.69***
		(0.20)		(0.17)		(0.14)
M-caste × FD		-1.37***		1.08***		-0.81***
		(0.23)		(0.22)		(0.15)
L-caste × FD		-1.16***		0.90***		-0.69***
		(0.23)		(0.22)		(0.15)
Observations	1,119,508	1,119,508	1,119,508	1,119,508	1,119,508	1,119,508
R-squared	0.51	0.13	0.55	0.23	0.46	0.09
District FE	✓	-	✓	-	✓	-
NIC4 FE	✓	✓	✓	✓	✓	✓

Notes: Results from the firm-level regression using equation 2. Dependent variables *arpk* and K/L are in logs and Profit Rate is IHS transformed and shown in column headings. *Fd* is an index of financial development across states. The variables *arpk* and K/L are the average products of capital and the capital-labor ratio. M-caste is the dummy variable for middle-caste enterprises and L-caste is the dummy variable for low-caste enterprises. All specification include gender of owner and religion fixed effects. The standard errors are in parentheses, clustered at the caste, state and sector level. Robust standard errors are in parentheses, clustered at the caste, region and sector level. To see the regression estimates with sampling weights, refer to Table B.9 in Appendix B. The results are qualitatively similar. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Calibrated Parameters and Matched Moments

Fixed	Value	Description
δ	0.06	Annual depreciation rate
α	0.33	Physical capital share: noncorporate sector
θ_c	0.33	Physical capital share: corporate sector
γ	1.50	Coefficient of risk aversion
κ_c	0.68	Share of total capital in corporate sector
ϕ_r	1.00	Credit supply shifter
d	0.033	Net interest rate margin
P_{lc}	0.29	Population share: LC
P_{mc}	0.39	Population share: MC

Fitted	Value	Description	Moments	Model	Data
λ_{hc}	3.97	Financial frictions HC	Overall Credit/output	0.44	0.44
λ_{mc}	2.08	Financial frictions MC	Rel. Credit/output	0.57	0.53
λ_{lc}	1.86	Financial frictions LC	Rel. Credit/output	0.49	0.48
ν	0.25	Span of control	Income distribution	See Figure 3a	
η	4.80	Scale Parameter productivity	Employment distribution	See Figure 3b	
ρ	0.92	Discount rate	Annual Interest Rate	5.7%	5.7%
			Capital-output ratio	2.14	2.04
ψ	0.90	Persistence in productivity	Exit rate	8.8%	9.3%
κ	0.35	Operating cost	Young rel. size	0.56	0.54
$\overline{K}$	87.1	Capital threshold MSME sector	Share of MSME sector	0.70	0.70

Note. The rel. Credit/output for MC is $\left(\frac{Credit}{output}\right)_{MC} \Big/ \left(\frac{Credit}{output}\right)_{HC}$, and the rel. Credit/output for LC is $\left(\frac{Credit}{output}\right)_{LC} \Big/ \left(\frac{Credit}{output}\right)_{HC}$. The income distribution is taken from IHDS (see Table A.2 in Appendix A.4). The data counterpart of employment share distribution is from the Economic Census (see Table 1). The share of the MSME sector in noncorporate sector is taken from Section 3.

Table 6: ARPK, Capital Intensity, and Firm Ownership

	Model	Data		Model	Data
Panel A. Intensive-Margin (MSMEs)					
$arpk$-MC	+21.6%	+13%(22%)	$sd(arpk)$-HC	0.44	1.36
$arpk$-LC	+24.0%	+25%(30%)	$sd(arpk)$-MC	0.58	1.22
Capital/Labor-MC	−21.6%	−26%(27%)	$sd(arpk)$-LC	0.59	1.22
Capital/Labor-LC	−24.0%	−49%(45%)			
Profitability-MC	+10.4%	+2%(10%)			
Profitability-LC	+11.7%	+5%(14%)			
Panel B. Extensive-Margin					
Share of enterprises-HC	40.8%	36.5%			
Share of enterprises-MC	34.5%	47.5%			
Share of enterprises-LC	24.6%	16.0%			
Panel C. Heterogeneity across firms					
Small firm: Lowest Decile	42%	52%			
Large firm: Top Decile	10%	12%			

Notes: The measures of $arpk$, capital-intensity(k/l), and profitability (π/y) are computed for MSMEs in both the data and the model and represent their respective values with respect to HC enterprises in the manufacturing sector. For $arpk$, k/l, and π/y, the table also contains, in brackets, the caste differences estimated using the regression model with a sampling multiplier. The firm ownership rates by each caste in the data is computed using the Economic Census 2005. For more details, refer to Table 3 on $arpk$ estimates and Table A.1b in Appendix A for the firm ownership rates and the employment shares. In Panel C, the measures of $arpk$ are computed for MSMEs in both the data and the model and represent their respective values with respect to HC entrepreneurs.

Table 7: Regional Financial Development and ARPK Differences

	Model					Data		
Financial Development	Lowest	Benchmark			Highest	Low	Medium	High
Regions	(i)	(ii)	(iii)	(iv)	(v)	(a)	(b)	(c)
Intermdiation cost	$d = 0$	$d = 0.03$	$d = 0$	$d = 0$	$d = 0$			
Regional credit shifter	$\phi = 0.6$	$\phi = 1$	$\phi = 1$	$\phi = 2$	$\phi = 3$			
Credit-output ratio	0.31	0.44	0.59	0.81	0.90	0.28	0.62	1.21
TFP	1.29	1.32	1.33	1.37	1.38			
$arpk$-MC	+30.6%	+21.6%	+23.2%	+12.7%	+8.7%	+19.1%	+13.0%	+8.4%
$arpk$-LC	+36.8%	+25.2%	+28.1%	+15.6%	+10.6%	+30.3%	+25.8%	+11.5%

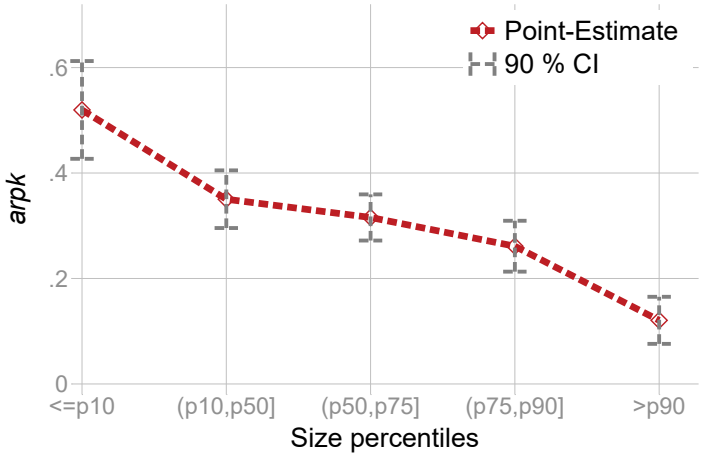
Notes: The measures of $arpk$ represent their respective values with respect to HC enterprises in the manufacturing sector. The financial constraint is given by $(1 + r_t + \delta + d)k_t \leqslant \phi\, \lambda_c\, a_t$. The $arpk$ differences are computed for all firms in the model. For data, I divide regions into three levels of financial development: low, medium and high and report the $arpk$ differences across castes.

Table 8: A Comparison of the Benchmark and Counterfactual Economy

	BM	CF	Change			
Panel A. Noncorporate sector						
TFP	1.32	1.37	+3.6%			
$\sigma(arpk)$	0.54	0.40	-26.7%			
Output per worker	1.80	1.92	+6.6%			
Capital Intensity	2.53	2.75	+9.0%			
Credit/Output	0.44	0.58	+32%			
Interest Rate	5.70%	6.20%	0.50 p.p.			
Panel B. Caste-Level						
	Middle-Caste			Low-Caste		
	BM	CF	Change	BM	CF	Change
Capital Intensity	2.46	2.75	12.0%	2.40	2.75	15%
Output per worker	1.80	1.92	+6.6%	1.80	1.92	+6.6%
Firm Ownership	34.5%	39.3%	+4.8 p.p.	24.6%	29.5%	+4.9 p.p.
Credit/Output	0.35	0.58	65%	0.30	0.58	93%
$\sigma(arpk)$	0.58	0.40	-30.0%	0.59	0.40	-33.2%

Note. This table compares the results between the benchmark economy (BM) and the counterfactual economy (CF). The output per worker and capital intensity are computed at the aggregate-level. The changes in firm-ownership rates and interest rates are in percentage points (p.p.), and $\sigma(arpk)$ is standard deviation in the ARPK.

(a) ARPK for Low Caste Enterprise over Size



(b) ARPK for Middle Caste Enterprise over Size

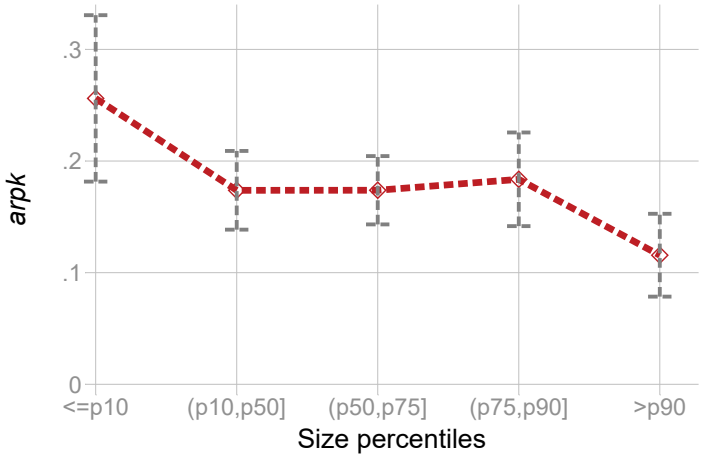


Figure 1: ARPK over Enterprise Size

Notes: This figures plots the evolution of ARPK over firm size (output). The size bins are defined as follows: (i) p10: firms below the 10th percentile, (ii) p10-p50: firms between the 10th and 50th percentile (iii) p50-p75: firms between the 50th and 75th percentiles, (iv) p75-p90: firms between the 75th and 90th percentile, and (v) p90: firms above the 90th percentile. I run regression specification 1 for each size bin and plot β_1 in Panel a, and β_2 in Panel b. The standard errors are clustered at the caste, state and sector level. To see the regression estimates with sampling weights, refer to Figure B.2 in Appendix B. The results are qualitatively similar.

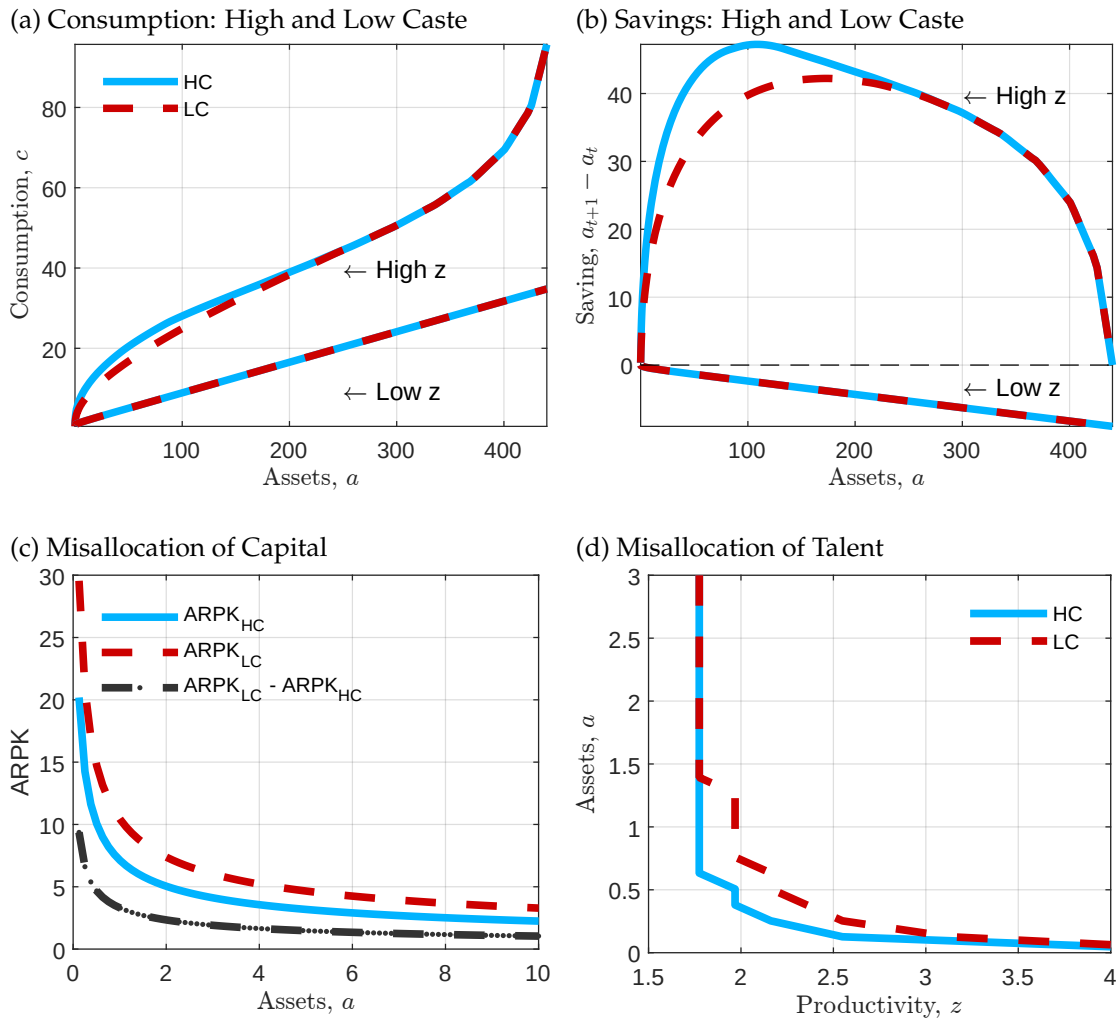


Figure 2: Consumption, Asset Growth and Misallocation across Castes: Model

Note. In the Panels (a) and (b), z represents productivity. The panels have policy functions for high productivity z and low productivity z households in the model. In Panels (c) and (d) I truncate the state space of productivity z and assets a to clearly highlight the cross-caste differences. Panel (c) presents the average revenue product of capital $arpk$ over assets for different castes. Panel (d) presents the occupation choice policy for every productivity z and assets a. The lines represent pairs (z, a) of marginal entrant on whose right everyone becomes an entrepreneur.

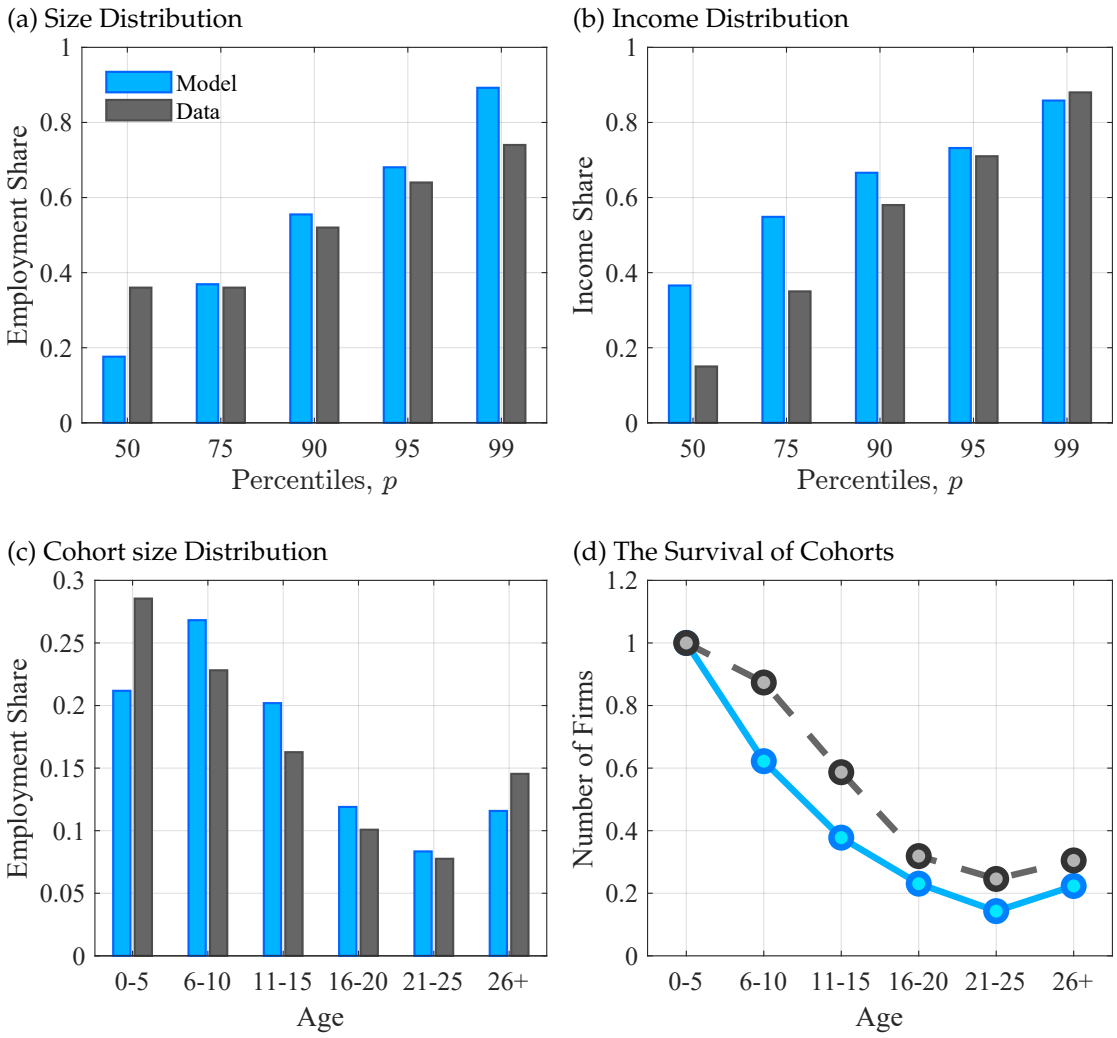


Figure 3: Distribution of Enterprises, Employment and Income

Note. Panel (a) shows the cumulative employment share distribution and Panel (b) shows the cumulative income distribution. Panel (c) contains the aggregate employment share of manufacturing establishments in India as a function of age and Panel (d) depicts the share of enterprises by age relative to the share of enterprises in the youngest age category (data points are taken from Akcigit, Alp, and Peters 2021).