



How does Caste Affect Entrepreneurship? Birth vs Worth

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Birth vs Worth

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Abstract

This paper examines the relative importance of the caste system in explaining the resource misallocation in India and quantifies its impact on aggregate productivity. I document that the historically disadvantaged castes (LC) are less likely to enter entrepreneurship even though they are more productive on average. At the intensive margin, the LC entrepreneurs are less capital-intensive but have higher marginal revenue product of capital relative to high castes. In a quantitative model of entrepreneurship, I find that the LC face higher entry cost and stricter financial constraints and that such asymmetries reduce aggregate TFP by 2.54% and output by 6%. (JEL Codes: O11 E23 D61)

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1 Introduction

Aggregate productivity differences across countries are very large (Hall and Jones 1999 and Caselli and Feyrer 2007). A large body of literature has argued that the misallocation of resources explains a substantial part of such differences—see, e.g., Banerjee and Duflo (2005), Restuccia and Rogerson (2008), Guner et al. (2008) and Hsieh and Klenow (2009). A number of market oriented distortions, such as financial frictions, labor market regulation, size-dependent policies, among others, have been proposed as being responsible for misallocation and lower aggregate productivity. However, there is a lack of systematic evidence about the quantitative importance of informal institutions in generating aggregate misallocation.

This paper quantifies the effects of one such institution, i.e., the caste system in India, on aggregate productivity. In particular, I explore the hypothesis that “birth and not worth”, i.e., caste instead of productivity, of individuals determine occupational choices and the way in which resources are allocated in the economy. Historically, the caste system sorted people into different occupations at birth and restrained any cross-occupation mobility. While mobility restrictions have weakened over time, the caste system remains a salient feature of the Indian society (Munshi, 2016).

I use a micro-level dataset to provide novel empirical evidence which is consistent with the presence of high levels of *caste-driven* resource misallocation. First, I show that the occupational choice of individuals is largely influenced by their caste. Historically disadvantaged castes (low castes), who were barred from entrepreneurship and were supposed to do menial jobs such as manual scavenging, skinning of dead animals, among others, are still less likely to be entrepreneurs even though they are more productive and profitable on average. Second, the allocation of capital across entrepreneurs is influenced by their caste. I show that the low-caste entrepreneurs are less capital-intensive and have higher returns on capital (i.e., higher MRPK).

Next, I develop a dynamic general equilibrium model that I use to evaluate the aggregate effects of these facts. In my model, heterogeneous agents that belong to different castes choose their occupation in the presence of caste-specific fixed cost of entry and financial frictions. Through the lens of the model, the differences in capital intensity and MRPK across castes are rationalized by higher fixed costs and tighter borrowing limits for low caste individuals. I find

that this asymmetry generates aggregate TFP and GDP losses of 2.54% and 6% respectively. Moreover, the model allows me to decompose the TFP losses into two margins. First, among the active entrepreneurs, the misallocation of capital across castes is responsible for 43% and 34% of the TFP and GDP losses respectively. Second, distortions in the economy that prevent productive but poor low-caste individuals to enter and allow unproductive high caste agents to operate explain the rest of the losses.

The empirical analysis exploits data from the Economic Census of India (EC) of 2005 and Micro, Small and Medium Enterprises (MSME) censuses of 2001 and 2006. These datasets provide the caste of the enterprise owner and employees, which allows me to compute the share of enterprises ownership, capital intensity and return on capital across castes. Using these datasets, I establish four main stylized facts.

First, historically disadvantaged castes (low caste) represent a smaller fraction of enterprises relative to their share in population. In 2005, low-caste entrepreneurs owned 13% of all the non-farm establishments in the country whereas their share in the population was 24%. Meanwhile, the high-caste entrepreneurs represented 44% of the establishments, but only made up 33% of the population. Moreover, the share of low-caste entrepreneurs is increasing in the labor intensity of the sectors. Next, I find that the average low-caste entrepreneur has 10% and 42% higher total factor productivity revenue (TFPR) and physical (TFPQ) respectively (TFPQ is measured for single product enterprises). Moreover, low castes are 9% higher profitability (profits/value-added) for the low-caste entrepreneurs relative to the high-caste entrepreneurs.

Second, within a sector, firms of low-caste entrepreneurs are less capital-intensive but have higher MRPK. I measure average returns on capital in the data, but interpret these as the marginal returns under the assumption of a Cobb-Douglas production function and perfect competition. The low-caste entrepreneurs in the Micro, Small and Medium Enterprises (MSME) census have 30% higher MRPK than that of the high caste entrepreneurs. A higher MRPK suggests a higher marginal cost of capital which in turn coerces the low-caste entrepreneurs to substitute capital with labor and results in lower capital intensity. Indeed, I find that low caste enterprises are 61% less capital-intensive relative to high-caste enterprises. [Hadlock and Pierce \(2010\)](#) argue that the small and young firms are financially constrained. In line with this liter-

ature, I also find that, within a cross-section, these differences in MRPK and capital intensity disappear as enterprises become larger and older.

Third, caste-dependent misallocation of capital represents a significant part of total misallocation. Following [Hsieh and Klenow \(2009\)](#), I use dispersion in the MRPK as a proxy for the misallocation of capital. I decompose this dispersion into across-caste and within-caste components. The sectoral mean and median of caste-dependent misallocation is 6% and 5% respectively (it varies from 1 to 25%). Moreover, I compute the caste-dependent misallocation of capital for different states in India and find that it is positively correlated with the strength of the caste system as proxied by within-caste marriage rates. Fourth, I use the MSME census of 2001 and 2006 to compute the average growth rate of capital for different cohorts of enterprises. The average growth rate of capital for low-caste entrepreneurs is 50% lower relative to those of high castes.

In order to rationalize these facts, I build a quantitative model of entrepreneurship based on [Buera and Shin \(2013\)](#), where agents from different castes can either choose to become entrepreneurs or workers in the context of *caste-dependent fixed cost of entry and financial constraints*. The model serves two main purposes. First, it helps me to disentangle the effects of misallocation of talent from misallocation of capital. Second, it incorporates a self-financing channel that allows productive entrepreneurs to increase their collateral-base over time by saving more in the present and postponing consumption to the future ([Banerjee and Moll 2010](#), [Midrigan and Xu 2014](#), [Moll 2014](#), [Buera et al. 2015](#), and [Buera et al. 2011](#)). In this model, the combination of lower borrowing limits and uncertainty about the future profits do not allow low-caste entrepreneurs to become fully unconstrained in the steady state. As a result, low-caste enterprises remain relatively more constrained in equilibrium, thus, generating a dispersion in MRPK across castes.

The quantitative predictions of the model depends on four crucial parameters: the fixed cost of entry for each caste and caste-dependent borrowing constraints. I calibrate the model to match certain moments in the data, especially, the entrepreneurial rates and the credit to value-added ratios. In the stationary equilibrium, the low-caste individuals face 80% higher fixed costs and 22% stricter borrowing limits. At the intensive margin, the model captures

approximately 56% of the difference in observed capital intensities and 85% of that in MRPK across castes. Higher MRPK implies that the low castes are more financially constrained and have lower leverage. At the extensive margin, the model captures around half of the differences in profitability and 35% of the differences in productivity (low caste being 4.1% more profitable and have 3.5% higher TFPR).

Finally, I perform two counterfactual exercises to highlight the importance of misallocation at the extensive and intensive margins. First, I equalize the MRPK across castes among the entrepreneurs who are operating in the steady state of the benchmark economy (this implies the number of entrepreneurs and the productivity distribution remain constant). This allows low-caste entrepreneurs to increase their capital intensity and as a result both size and the labor productivity improve. The reallocation of capital from unproductive high-caste entrepreneur towards low-caste entrepreneurs raises the TFP of the economy by 1.03%. Next, I also allow for the entry of productive low-caste entrepreneurs who could not enter before because of high fixed cost or small borrowing limits. This improved selection of entrepreneurs raises the average productivity of entrepreneurs by 4%. However, the number of entrepreneurs decreases by 4% because the cost of capital, i.e., interest rate, increases by 13% due to higher demand for capital. Due to the improvements in labor productivity (4% relative to the benchmark), the wage is also higher. This encourage the marginal entrepreneurs to exit. As a result, the overall TFP of the economy improves by 1.51%.

Literature review: This paper contributes to the literature on the misallocation of resources. [Banerjee and Duflo \(2005\)](#), [De Mel et al. \(2008\)](#), and [Hsieh and Klenow \(2009\)](#) document large dispersions in the marginal product of capital across establishments in developing countries.¹ More specifically, there are a number of papers that relate ethnic heterogeneity and misallocation. [Hsieh et al. \(2013\)](#) argue that race-based and gender-based distortions affect the allocation of talent in the US. [Erosa et al. \(2017\)](#) argue that misallocation of talent across occupations has significant aggregate effects on productivity. [Hjort \(2014\)](#) explores the role of

¹More generally, there is a vast literature that studies the effects of resource misallocation: [Banerjee and Moll \(2010\)](#), [Buera et al. \(2011\)](#), [Song et al. \(2011\)](#), [Buera and Shin \(2013\)](#), [Midrigan and Xu \(2014\)](#), [Hopenhayn \(2014\)](#), [Moll \(2014\)](#), [Buera et al. \(2015\)](#) and [Restuccia and Rogerson \(2017\)](#). Papers on misallocation in India: [Ghani et al. \(2012\)](#), [Hsieh and Klenow \(2014\)](#), [Garcia-Santana and Pijoan-Mas \(2014\)](#), [Duranton et al. \(2015b\)](#), [Duranton et al. \(2015a\)](#) and [Asturias et al. \(2016\)](#).

ethnic heterogeneity in distorting the allocation of resources within an establishment. [Banerjee and Munshi \(2004\)](#) document inefficiencies in the allocation of capital across communities in the Knitted Garment Industry in Tirupur (India), and [Villanger \(2015\)](#) evaluates the role of the caste system on entrepreneurship in rural Nepal. I contribute to this literature by quantifying the *aggregate* effects of caste-specific misallocation of capital and talent.

This paper also builds on the work of [Thorat and Sadana \(2009\)](#), [Iyer et al. \(2013\)](#) and [Deshpande et al. \(2013\)](#) who document substantial caste differences in entrepreneurship rates, employment and growth rates in India. I take their analysis one step further and document caste disparities in the scale and capital intensity in the MSME sector. [Jodhka \(2010\)](#) reports borrowing constraints as a major obstacle for the low-caste entrepreneurs (self reported by the respondents). [Fisman et al. \(2017\)](#) provide evidence on the importance of caste match between lender and borrower for the access of credit.² This paper formalizes the idea of caste specific borrowing limits or financial constraints in a parsimonious way and quantifies its impact on aggregate outcomes.

This paper also relates to the long-standing literature that explores the role of ethnic heterogeneity and economic prosperity, e.g., [Easterly and Levine \(1997\)](#), [Alesina and Ferrara \(2005\)](#), and [Montalvo and Reynal-Querol \(2005\)](#).

The remainder of the paper is organized as follows: Section 2 describes the caste system. Section 3 describes the data used in this paper. Section 4 presents the partial equilibrium model and documents the main stylized facts on misallocation. Section IV introduces the general equilibrium model and discusses the calibration strategy and the results. Section V concludes.

2 Institutional setup: The caste system

The caste system is a form of social stratification which divides people into rigid hierarchical groups based on their occupation. For centuries, caste dictated customary social interaction, exclusion and endogamy. [Bidner and Eswaran \(2015\)](#) have describe it as a 3,500 year old

²[Fisman et al. \(2017\)](#) find that a lender of certain caste increases credit access and reduces collateral requirements for the borrower of same caste. In general, it is more likely that an owner of bank, bank manager or a loan officer is a high caste individual (in their sample, 74% of the lenders belong to high caste). This implies that low and middle caste individuals are more likely to face unfavorable loan conditions in the form of stricter borrowing limits.

system within the context of the four principal castes also known as varnas ([Deshpande 2010](#)). Figure 1 in Appendix A.1 provides the caste structure in detail. In order of hierarchy, these are the Brahmins (priests and teachers), Kshatriyas (rulers and soldiers), Vaisyas (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 “Untouchables,” today better known as Dalits, associated with occupations such as manual scavenging or skinning of dead animals, among others. In the Indian constitution, Dalits fall under the category of “Scheduled Castes” since 1947, which is an officially designated group of historically disadvantaged people. The second group of people is known as “Scheduled Tribes.” They have been subjected to various forms of discrimination and fall well behind in terms of socio-economic indicators.

For the remainder of the paper, I ignore the micro-structure of the caste system and primarily focus on a very broad definition, i.e., the low-caste individuals are denoted by ‘LC’, which includes the Schedules Castes and Schedules Tribes; middle-caste are individuals denoted by ‘MC’ and includes the Sudras (also known as Other Backward Castes, OBC, which fall between the traditional upper castes and the lowest), and the high caste is denoted by ‘OTH’, which includes the top three castes: Brahmins, Kshatriyas and Vaishyas (including several religions as well).³

The castes differ in many dimensions,⁴ however, I focus on two particular margins, i.e., occupational choice and access to credit markets. [Thorat \(2004\)](#), and [Thorat and Newman \(2007\)](#) argue that the division of occupations under the caste system operates through inter-caste restrictions in land, labor and capital markets. This paper, in a general equilibrium setting, argues that low-caste individuals pay higher entry cost and face stricter borrowing limits due to imperfect access to credit markets. Higher entry cost is interpreted as the substantially higher barriers to entry for the low caste such as, bureaucratic hurdles in the form bribes, fear of being

³Traditionally, the caste system has been part of Hinduism but in modern India we do find its presence in other religions as well. [Neuman \(1981\)](#) describes the caste and social stratification among Muslims in India. [Jodhka \(2004\)](#) and [Puri \(2003\)](#) study the caste system in Sikhism. Recently, the catholic church also acknowledged the presence of caste based discrimination in their report: [Policy of Dalit Empowerment in the Catholic Church in India- An Ethical Imperative to Build Inclusive Communities](#).

⁴[Nayak and Prasad \(1984\)](#), [Banerjee and Knight \(1985\)](#), [Desai and Dubey \(2012\)](#), [Hnatkovska et al. \(2012\)](#), [Borooah et al. \(2014\)](#).

outcast on switching their traditional occupation, lack of access to entrepreneurial networks. Tighter borrowing limits could be a result of statistical or taste-based discrimination.

3 Description of the Data

In my empirical analysis I use data from the 2005 Economic census of India and from the Micro, Small and Medium Enterprises (MSME) census of 2001 and 2006. These datasets are not as commonly used as the Annual Survey of Industries or the CMIE Prowess. The main reason that researchers do not use the economic census more frequently is that it does not provide balance sheet information of the enterprise and also lacks a panel dimension, while the MSME census does provide balance sheet information, it omits large firms and does not have a panel dimension either. However, unlike the ASI and CMIE Prowess databases, the economic and MSME censuses do provide the caste of the private enterprise owner, which is a crucial information for this paper.

Economic Census 2005: The 5th Economic census in 2005 covered agricultural (excluding crop-production and plantation) and non-agricultural activities within the geographical boundary of India. In total, there are 42 million enterprises employing 99 million individuals. The manufacturing and services sectors represent 84.7 % of all the enterprises that employ 88.5 % of the total labor force. As far as the caste-based firm ownership is concerned, the Scheduled Castes and Scheduled Tribes (LC) own and operate 5.67 million of the firms, the middle caste (MC) operates more than 18 million of them and, similarly, 18 million of the enterprises are owned by the high caste (OTH). Following [Iyer et al. \(2013\)](#), I keep 19 large states of India that constitute 95 % of all the enterprises and 96 % of the population.⁵ The summary statistics of the data are available in panel A of Appendix Table 10.

MSME Census: The MSME dataset consists of two parts: a census of registered MSMEs and a survey of unregistered MSMEs.⁶ In total, the dataset includes 1.6 million observations

⁵The states include:- Andhra Pradesh, Assam, Bihar, Chhattisgarh, Gujarat, Haryana, Himachal Pradesh, Jharkhand, Karnataka, Kerala, Maharashtra, Madhya Pradesh, Orissa, Punjab, Rajasthan, Tamil Nadu, Uttar Pradesh, Uttarakhand and West-Bengal.

⁶Registration under Factories Act 1948-“Registration of manufacturing units is mandatory under Sectors 2m (i) and 2m (ii) of the Factories Act. Section 2m (i) refers to units engaging 10 or more workers and using power whereas 2m (ii) refers to units engaging 20 or more workers and not using power. Besides, some of the State

and provides the geographical information, industry classification, balance sheet variables and the caste of the owner. There are two measures of capital stock in the data: the original value of investment in plant and machinery, and the market values of fixed assets. The total wage bill includes salaries and wages, allowances, bonus, etc. The amount of loan outstanding captures all the loans from institutional and non-institutional sources. The variable ‘repayment delays’ captures all enterprises that have delayed the payment for principal or the interest for more than 12 months as of 31st March 2007. After dropping missing values and publicly owned enterprises, 1.5 million observations are available in 2006 and around 1.3 million for 2001 cross-section (also known as SSI census).

4 Stylized Facts

Fact 1: The Entrepreneurial Rate is lower but productivity is higher for low caste individuals

Entrepreneurial Rate: The enterprise ownership across castes is measured with the Economic census of 2005. The caste of the private enterprise is identified with the caste of its owner (public firms are dropped). I use the population census of 2001 and the National Sample Survey 66th Round 2009-10 to compute the low caste and the middle caste population shares respectively. The first two columns of Table 1 show that the low-caste individuals represent 24% of the total population, while they only own 13 % of all non-agricultural enterprises. Moreover, as shown in columns 3 and 4, low caste individuals own 14 % of the single employee enterprises, 1 percentage point higher than their overall ownership, and own 10% of the enterprises that hire labor outside of their family. In terms of employment, column 5, low castes employ around 11% of the total labor force.

Governments notify certain industrial activities for mandatory registration, although they do not conform to the criteria laid down under Sectors 2m (i) and 2m (ii). Such registrations are done under Section 85 (i) or Section 85 (ii) by the concerned State Governments. Section 85 (i) refers to units engaging less than 10 workers and using power and Section 85 (ii) refers to units engaging less than 20 workers and not using power.” Source-<http://www.dcmsme.gov.in/ssiindia/census/ch2.htm>. The Unregistered SSI sector for the purpose of Third Census has been defined as the set of all those units (SSIs, ancillaries and SSSBEs) which were eligible to be registered as on 31st March 2001, but were not permanently registered because the registration was voluntary. Service enterprises are not required to register, (Ghani et al. (2014))

Table 1: Share of Population and Non-agricultural Enterprises across castes

	(1)	(2)	(3)	(4)	(5)
Caste	Population	Enterprises	Enterprises with		Employment
			One employee	Outside labor	
LC	24%	13%	14%	10%	11%
MC	43%	43%	44%	10%	39%
OTH	33%	44%	42%	50%	50%

Notes: The enterprise ownership rates are computed with non-agricultural enterprises in the Economic census 2005. The population statistics for the low- and middle-caste are drawn from Census 2001 and National Sample Survey 66th Round 2009-10. Outside labor means labor outside the household.

The entrepreneurship intensity is measured by the ratio of share of enterprises of a certain caste group to its share in the population. In 2005, entrepreneurship intensity was 0.57, 1 and 1.3 for LC, MC and OTH respectively. Given that, as argued in the literature ([Deshpande et al. 2013](#)), self-employment can be more of a survival activity rather than entrepreneurship, I also compute the entrepreneurship rates excluding single employee enterprises. Then, the entrepreneurship intensity is 0.46, 0.96 and 1.43 for LC, MC and OTH respectively. While entrepreneurship intensity is significantly lower than one for low caste agents in all the states, there are some regional differences: Assam (1.06), West Bengal (0.79), Odisha (0.79), Himachal Pradesh (0.70) and Maharashtra (0.69) are the states with the highest entrepreneurial rate whereas Gujarat (.31), Jharkhand (0.34), Bihar (0.40), Rajasthan (0.45) and Madhya Pradesh (0.45) are the lowest.

Next, I compute the fraction of low-caste entrepreneurs at the sector level. If low-caste individuals face financial constraints or they do not have enough collateral to invest in plant and machinery then they should be relatively less likely to enter capital intensive sectors. I find a positive correlation between the fraction of firms owned by low caste and the labor intensity of the sector as depicted in Figure 6. The labor intensity is proxied by the share of wages in sectoral value-added in the U.S. manufacturing sector. Moreover, this correlation becomes even stronger if I consider enterprises with more than one employee (non-self employed).

Productivity differences across castes: I use three different measures of productivity, i.e., TFPR, TFP and Profitability. To compute these measures, I assume production technology to be Cobb-Douglas with capital and labor as production factors. Measuring firm-level productivity requires a panel dataset of firms that I lack at this point of time. Therefore, I measure

$TFPR := \frac{Y_i}{K_i^\alpha L_i^{1-\alpha}}$, Y_i is value-added, K_i is capital stock and L_i is wage bill for enterprise i . α is sector specific. Similar to [Hsieh and Klenow \(2009\)](#) (in the context of constant returns to scale technology), and [Da-Rocha et al. \(2017\)](#) and [Hopenhayn \(2014\)](#) (in the context of decreasing return to scale technology), TFPR is a measure of product of firm-level prices and productivity.

I use the wage bill as the labor input. In order to compute within sector differences I use the regression model shown:

$$\log Y_i = \beta_0 + \beta_1 \mathbb{1}_{L-CASTE} + \beta_2 \mathbb{1}_{M-CASTE} + \Gamma_i + \varepsilon_i. \quad (1)$$

The dependent variables are $Y_i \in \{TFPR, TFP, profitability\}$. The main explanatory variables are the dummies for the low-caste entrepreneurs, $\mathbb{1}_{L-CASTE}$, and the middle-caste entrepreneurs, $\mathbb{1}_{M-CASTE}$, whose corresponding coefficients are β_1 and β_2 . The estimators $\hat{\beta}_1$ and $\hat{\beta}_2$ are interpreted as the log points difference in the dependent variable between the low- and high-caste entrepreneurs, and the middle- and high-caste entrepreneurs respectively. Additionally, there is a vector of controls, Γ_i , that includes region, gender and religion FE, enterprise-level wage, share of own-caste workers, proxy for human capital (average years of schooling), average land holdings and volatility of growth rate of value-added at caste-sector-region level. First, as row 1 in [Table 2](#) shows, TFPR is 10% higher for the low-caste entrepreneurs relative to the high-caste entrepreneurs within a sector. However, the middle-caste has a similar level of TFPR in comparison to the high-caste entrepreneurs. As discussed earlier, TFPR is a product of firm productivity and prices. Therefore, the product market distortions that correlated with caste may be reflected in the prices and hence in the TFPR as well. In order to overcome this issue, I use a quantity based measure of output to compute total factor productivity (TFP) for enterprises that produce only one product. Here, I use product FE instead of sector FE to get rid of unobserved product market heterogeneity. The results in, row 3 [Table 2](#), suggests that TFP is 42% higher for low castes and 26% higher for middle castes.

Next, I run the regression for the measure of *Profitability*, which is defined as the ratio of profits to value-added. The profitability is defined as $\pi_i = \frac{Y_i - rK_i - wL_i}{Y_i}$, where r is interest rate and assumed to be 6%. In my data, there are many observation with negative profitability. I use a IHS transformation of the profits as suggested in [Bellemare et al. \(2013\)](#). I find the low-caste

entrepreneurs to be 9% higher profitability relative to the high-caste entrepreneurs, row 2 Table 2. Such evidence suggests that very selected low-caste agents are entering the market. In the next section, I examine how the caste dependent capital market distortions affects the capital allocation at the intensive margin.

Table 2: Caste differences in productivity: 2006

	M-caste	L-caste	Sector-FE 4-digit	Product-FE 5-digit	Region-FE	Set of controls	Obs. (Millions)	Adj. R-squared
log(TFPR)	0.006 (0.028)	0.102 (0.058)	Yes	No	Yes	Yes	1.3	0.363
log(π)	0.030 (0.024)	0.086 (0.038)	Yes	No	Yes	Yes	1.3	0.464
log(TFP)	0.262 (0.029)	0.420 (0.233)	No	Yes	Yes	Yes	0.3	0.306

Notes: Results from the enterprise level regression using equation 1. Dependent variables are shown in the first column: TFPR, π (profitability) and TFP. M-caste is the dummy variable for the middle-caste enterprises. L-caste is the dummy variable for the low-caste enterprises. TFPR is total factor productivity revenue, TFP is physical productivity and profitability is the ratio of profits to value-added. All dependent variables are in logs except for profitability. I use a IHS transformation of the profitability as suggested in [Bellemare et al. \(2013\)](#). The vector of controls, Γ_i , that includes region, gender and religion FE, enterprise-level wage, number of own-caste employees, proxy for human capital (average years of schooling), average land holdings and volatility of growth rate of value-added at caste-sector-region level. There are 211 sectors at 4-digit and 6000 products at 5-digit classification. Table 7 in Appendix provides results for sector-FE at 5-digit classification (611 in total). The standard errors are in parentheses, clustered at caste-region level.

Fact 2: Capital Intensity is lower and MRPK is higher for low caste entrepreneurs

Estimates of misallocation at the intensive margin are model specific and crucially depend upon the assumption that one makes about the production technology. First, I assume the production function to be Cobb-Douglas, which makes the average revenue product of capital proportional to the marginal revenue product of capital (MRPK). Second, profit-maximizing enterprises equate their MRPK to the interest rate. These two assumptions together imply that there is no dispersion in the MRPK in the economy. Following [Hsieh and Klenow \(2009\)](#), dispersion in the MRPK is attributed to the misallocation of capital. However, I am only interested in the dispersion generated by caste-specific distortions. As the low-caste entrepreneurs face considerable constraints in the capital market, one would expect their MRPK to be higher and as a consequence their capital-labor ratio to be lower relative to the high-caste entrepreneurs.

Such differences generate dispersion in MRPK across castes. Therefore, I compute the average MRPK and capital-labor ratio across and within sectors for each caste while controlling for some measures of unobserved heterogeneity. It is important to note that I measure average revenue product of capital in the data and interpret it as MRPK using the model.

In the model, there is a continuum of agents that differ in their productivity, z . All agents own and operate an enterprise and have access to diminishing returns to scale technology, (Lucas Jr 1978). They take the wage and the interest rate as given and choose the optimal level of capital and labor (a GE version with endogenous factor prices and occupation choice is discussed in the next section).

The profit maximization problem for enterprise i of caste c operating in sector s with productivity z_{sci} is given by:

$$\max_{L_{sci}, K_{sci}} \left\{ z_{sci} (K_{sci}^{\alpha_s} L_{sci}^{1-\alpha_s})^{1-\nu} - w L_{sci} - (1 + \tau_{Ksc}) r K_{sci} \right\}, \text{ where} \quad (2)$$

Y_{sci} is gross value added, K_{sci} is the capital stock (market values of fixed assets) and L_{sci} is the labor input (measured as employment). Employment is an imperfect of labor input as it fails to capture actual hours worked and quality. In the regression later, I control for average wage paid by firms to rule out such concern. w is wage rate (same for all castes) and r is interest rate. The capital share α_s and the span of control parameter $1 - \nu$ are assumed to be 0.3 and 0.8 respectively.⁷ I denote caste-specific distortions that raise the marginal product of capital relative to labor for a certain caste group as the τ_{Ksc} . For example, one would expect a higher τ_{Ksc} for the low-caste entrepreneurs that lack proper access to credit and a lower τ_{Ksc} for the high-caste entrepreneurs who have access to cheap credit.

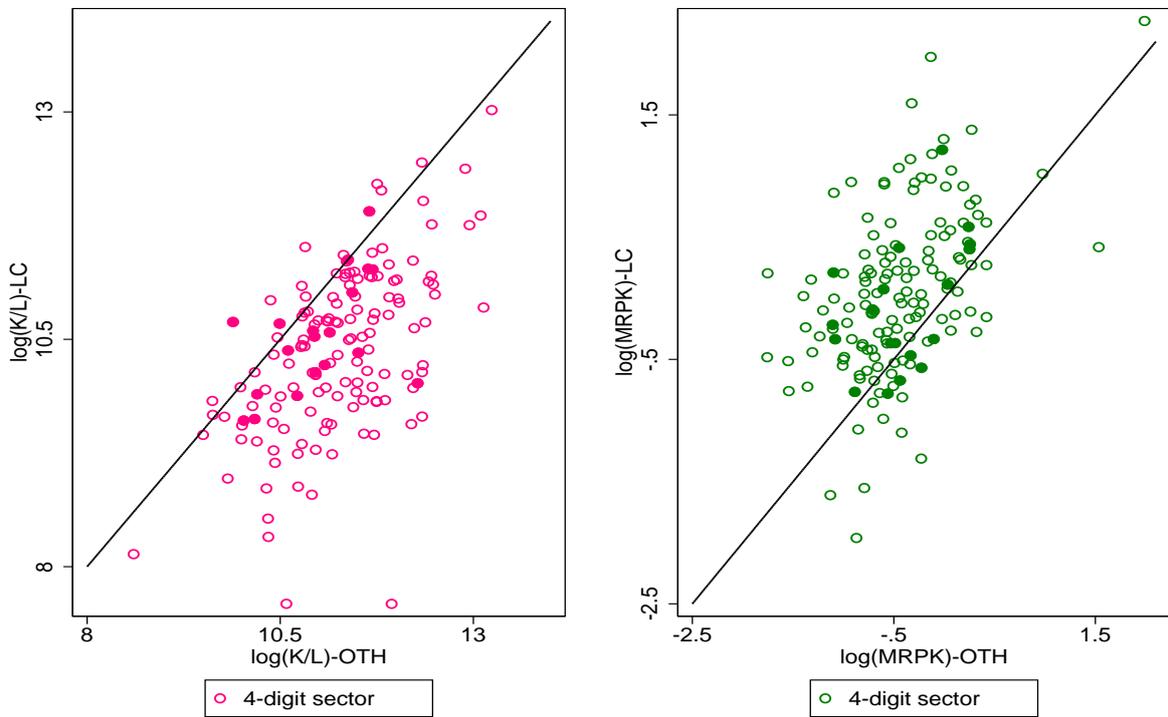
The first order condition (FOC) with respect to capital gives the MRPK and that combined

⁷ Atkeson and Kehoe (2005) chose $1 - \nu \geq 0.8$. In case of α_s , I also perform robustness checks with different sectoral capital shares in Indian manufacturing. Moreover, following Hsieh and Klenow (2009), I also compute MRPK with US sectoral capital shares. The choice of α_s affects the estimates for across caste differences in MRPK and K/L , while within sector differences remain unchanged and this paper primarily focuses on the later.

with the FOC with respect to labor gives the optimal capital-labor ratio or capital intensity.

$$\begin{aligned} \text{MRPK}_{sci} &:= \alpha_s (1 - \nu) \left(\frac{Y_{sci}}{K_{sci}} \right) = (1 + \tau_{Ksc}) r, \\ \text{MRPL}_{sci} &:= (1 - \alpha_s) (1 - \nu) \left(\frac{Y_{sci}}{L_{sci}} \right) = w, \\ \left(\frac{K}{L} \right)_{sci} &:= \left(\frac{\alpha_s}{1 - \alpha_s} \right) \left(\frac{1}{1 + \tau_{Ksc}} \right) \frac{w}{r}. \end{aligned}$$

Figure 1: Capital intensity & MRPK across sectors: 2006



Notes: The capital-labor ratio and log(MRPK) are calculated by using MSME census 2006. Each circle represents a 4 digit sector (211 in total). The dots represent sectors such as food products and beverages (NIC-15), tanning and dressing of leather; manufacture of luggage, handbags, saddlery, harness and footwear, apparels or furniture (NIC-18,19). Sampling weights are applied.

Sector differences: In order to measure the MRPK and capital intensity (capital-labor ratio), I use the MSME database for the fiscal year 2006.⁸

Figure 1 plots the capital-labor ratio and the MRPK for each sector (211 sectors in total) and for each caste (LC and OTH). From the graphs, it is evident that differences in capital intensity and MRPK exist in most of the sectors although there is a lot of heterogeneity.⁹ Moreover,

⁸The MSME data is only available for 2006 and not for 2005. In the MSME dataset, low caste agents own and operate 16% of the firms, much higher than the Economic census because low-caste enterprises are smaller and more likely to be captured by MSME census.

⁹The sectors are defined according to the national industry classification 2004 (NIC

differences persist in sectors such as food products and beverages, tanning and dressing of leather; manufacture of luggage, handbags, saddlery, harness and footwear, apparels where the enterprise ownership of low castes is quite substantial (these sectors are represented by dots and all the rest by circles); e.g., tanning and dressing of leather, stigmatizing job traditionally associated with low castes, one can observe large disparities in capital intensity (1 log point lower) and MRPK (0.3 log points higher).

Cross-sectional regressions: In order to compute the average within and across sector differences I use the regression model in equation 1, where the dependent variables are $Y_i \in \{K/L, MRPK\}$.

The resulting caste-specific estimates suggest that the low- and middle-caste entrepreneurs are 83% and 43% less capital-intensive, whereas their MRPKs are 18% and 43% higher relative to the high-caste entrepreneurs (OTH), respectively, across sectors. However, when I control for sector fixed effects (columns 2 and 5), the differences drop by 25% but still remain quite large. I use a 4-digit sector classification in the main table but regression results with a 5-digit classification are available in Table 7. These results suggest that the low- and middle-caste entrepreneurs are more likely to operate in less capital intensive sectors and this seems reasonable given that they have potentially limited access to capital markets, which makes labor oriented activities more lucrative to them.

Robustness

In this section I discuss various factors that could correlate with caste and bias the estimates of β_1 and β_2 but, in principle, are not due to capital market distortion.

It is well established that low castes are poorer and less educated than the high castes on average. This may lower their ability to access the credit in the financial markets. In the regression specification 3 & 6 of Table 3, I control for average years of schooling and the average land-holdings at the caste-region-sector level. These controls are measured by using employment-unemployment survey of 2008-09 provided by [Minnesota Population Center](http://mospi.nic.in/classification/national-industrial-classification/national-industrial-classification-2004) 2004, <http://mospi.nic.in/classification/national-industrial-classification/national-industrial-classification-2004>). There are 211 sectors at 4-digit level. Figure 7 provides the graph at 5-digit sector classification with 633 sectors.

Table 3: Capital intensity and MRPK across and within sectors: 2006

Dependent variables:	(1) k/l	(2) k/l	(3) k/l	(4) mrpk	(5) mrpk	(6) mrpk
M-caste	-0.431 (0.054)	-0.329 (0.049)	-0.230 (.028)	0.184 (0.041)	0.135 (0.040)	0.121 (.028)
L-caste	-0.836 (0.058)	-0.616 (0.049)	-0.409 (.048)	0.429 (0.048)	0.305 (0.044)	0.285 (0.47)
Sector-FE	No	Yes	Yes	No	Yes	Yes
Region-FE	Yes	Yes	Yes	Yes	Yes	Yes
Gender & Religion-FE	Yes	Yes	Yes	Yes	Yes	Yes
Set of controls	No	No	Yes	No	No	Yes
Obs(Million)	1.5	1.5	1.3	1.5	1.5	1.3
Adj. R-squared	0.419	0.480	0.525	0.427	0.454	0.463

Notes: Results from the enterprise level regression using equation 1. Dependent variables are in logs and shown in column headings. k/l is capital intensity and $mrpk$ is marginal revenue product of capital. M-caste is the dummy variable for the middle-caste enterprises. L-caste is the dummy variable for the low-caste enterprises. The vector of controls, Γ_i , that includes region, gender and religion FE, enterprise-level wage, number of own-caste employees, proxy for human capital (average years of schooling), average land holdings and volatility of growth rate of value-added at caste-sector-region level. The standard errors are in parentheses, clustered at caste-region level.

(2018). The results (row 3 and 6) show that half of the differences in the capital-labor ratio are absorbed by these controls but that the remaining differences between castes are still large and significant.¹⁰

Within a sector, these differences could emerge if the low-caste entrepreneurs do not have access to high-skilled labor that can operate machines. I control for the average wage of workers for each enterprise to get rid of differences in capital intensity and MRPK that are not driven by caste-specific capital market distortions.

Moreover, entrepreneurs in my dataset also hire workers from their own caste. Almost 70% percent of the workers belongs to the same caste as the entrepreneur, Table 9. This proportion of same-caste workers do decreases as the enterprise size increases, as seen in Figure 8. This fact could potentially bias the estimates of β_1 and β_2 . In order to control for such distortions, I include the proportion of own-caste workers at the establishment level in the regression but still large differences in the capital intensity and MRPK remain.

In the model presented above I consider only a capital distortion τ_K that raises the marginal

¹⁰In the model discussed earlier, I assumed that capital shares (α_s) are same across castes. I assume that all castes use same production technology.

product of capital relative to the labor. I do so to highlight the importance of such distortions in explaining the differences in MRPK. In principle, one could include output distortions τ_Y that could also potentially generate dispersion in MRPK as well. However, such distortions would increase the marginal products of capital and labor by the same proportion, something I do not find in the data. When I use $\log(\text{MRPL})$ as the dependent variable in the regression model as discussed above (equation 1) I do not find any significant within-sector differences across castes (see Appendix Table 7).

The product market distortions that correlated with caste may be reflected in prices and hence in the MRPK as well. Similarly, differences in markups can result in differences in MRPK and not necessarily imply any sort of capital misallocation. However, the markups will bias the measure of MRPL in the same direction as of the MRPK (as both are revenue based measures). In the data, I do not find any significant differences in MRPL.

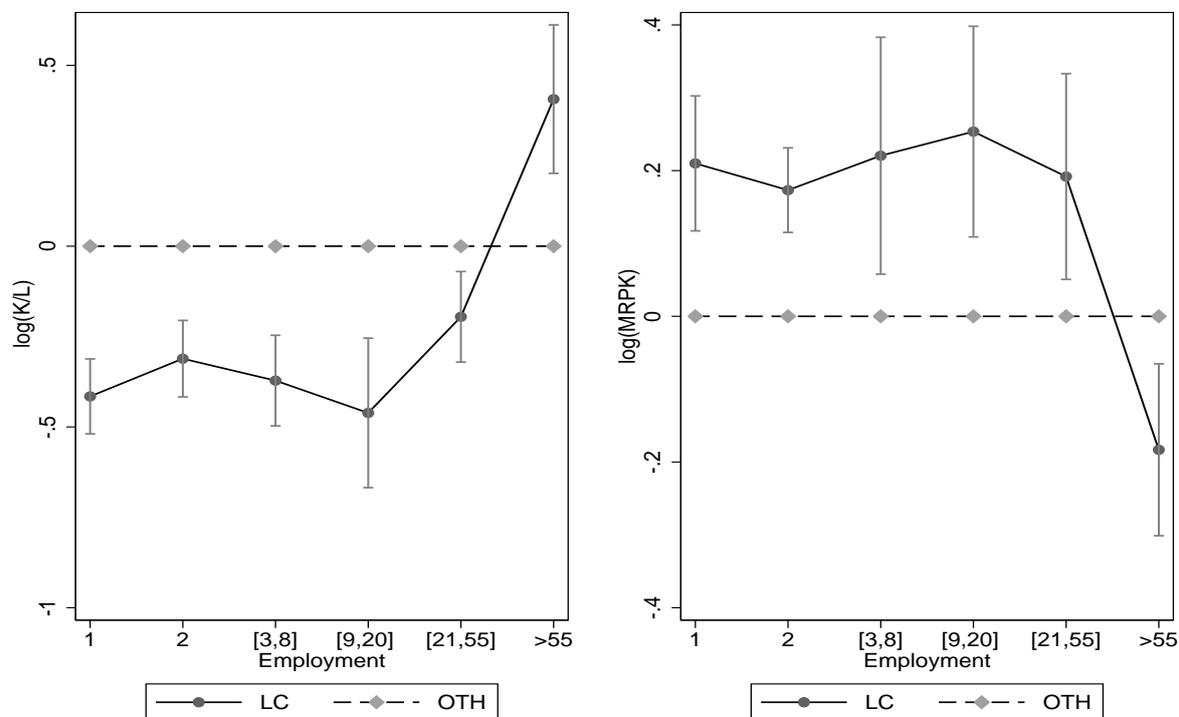
As a further robustness check, I use a quantity-based measure of output to compute the marginal product of capital (MPK) and marginal product of labor (MPL), instead of MRPK and MRPL, for firms producing only one product. Here, I use product FE instead of sector FE to control for any product-specific characteristic correlated with caste-specific distortions. The results in Table 8 (columns 4 and 5) suggests that the MPK is 40% higher for low-caste and 23% higher for middle-caste entrepreneurs, whereas the MPL is also higher but not significantly so for low-caste entrepreneurs.

In an economy where investment in the low-caste enterprises is more risky, higher MRPK would be a result of a higher risk premium demanded by the investors. One measure of risk is the *default rate*. However, the default rate depends on the leverage (credit/assets) at the enterprise level. I do not find any difference in default rates across different levels of leveraging. Furthermore, the differences in capital intensity and MRPK still emerge if one compares enterprises with the same level of leveraging.

The second measure of risk is the *dispersion in the growth rate of output*. The MSME census also provides data on the past two years of value-added for the enterprises that survive. This allows me to compute the average growth of value-added at the enterprise-level. Overall, conditional on survival, the growth rate is lower for low caste. Moreover, I compute the dispersion

in growth rate at the caste-sector-region level find it to be lower for low-caste. Meanwhile, the differences in capital intensity and MRPK remain unchanged if I control for such dispersion.

Figure 2: Capital-intensity & MRPK across size: 2006



Notes: Coefficients of the low caste dummy from regressions of $\log(k/l)$ (on the left) and $\log(\text{MRPK})$ (on the right) using specification 3 and 6 in Table 3 for each employment bin on the X-axis.

Controlling for firm size: In an economy where production technology involves a fixed cost, the lower scale of the low-caste entrepreneurs could be responsible for their lower capital-intensity and higher MRPK. Moreover, the presence of non-convexity in the production technology in capital-usage could also lead to such differences.

In order to overcome these concerns, I divide enterprises into five different size bins, defined by employment.¹¹ As shown in Figure 2 below, differences persist among smaller enterprises but they converge as the enterprise size becomes large. In fact, if one looks at enterprises with more than 55 employees, the low-caste entrepreneurs have higher capital-labor ratios than high-caste entrepreneurs, although such firms are very limited in number. This suggests that there is no difference between large low- and high-caste enterprises. In other words, the size of the firm may be sufficient to overcome caste distortions. This narrative fits perfectly into the

¹¹Results remain unchanged if I use value-added as a measure of size.

hypothesis of financial frictions. Low-caste entrepreneurs face stricter borrowing limits that constraint their growth and drive up their MRPK, whereas large firms have enough collateral to fund their capital needs, which enables them to operate at an optimal level of capital-intensity.

Controlling for firm size and age: It could be argued that the differences in the capital intensity and MRPK are driven by young low-caste entrepreneurs who are still in transition phase. There has been a surge in the entrepreneurship in India since the market friendly reforms of 1991. It may have incentivized the low-caste individuals to enter entrepreneurship and take advantage of the deregulated environment.

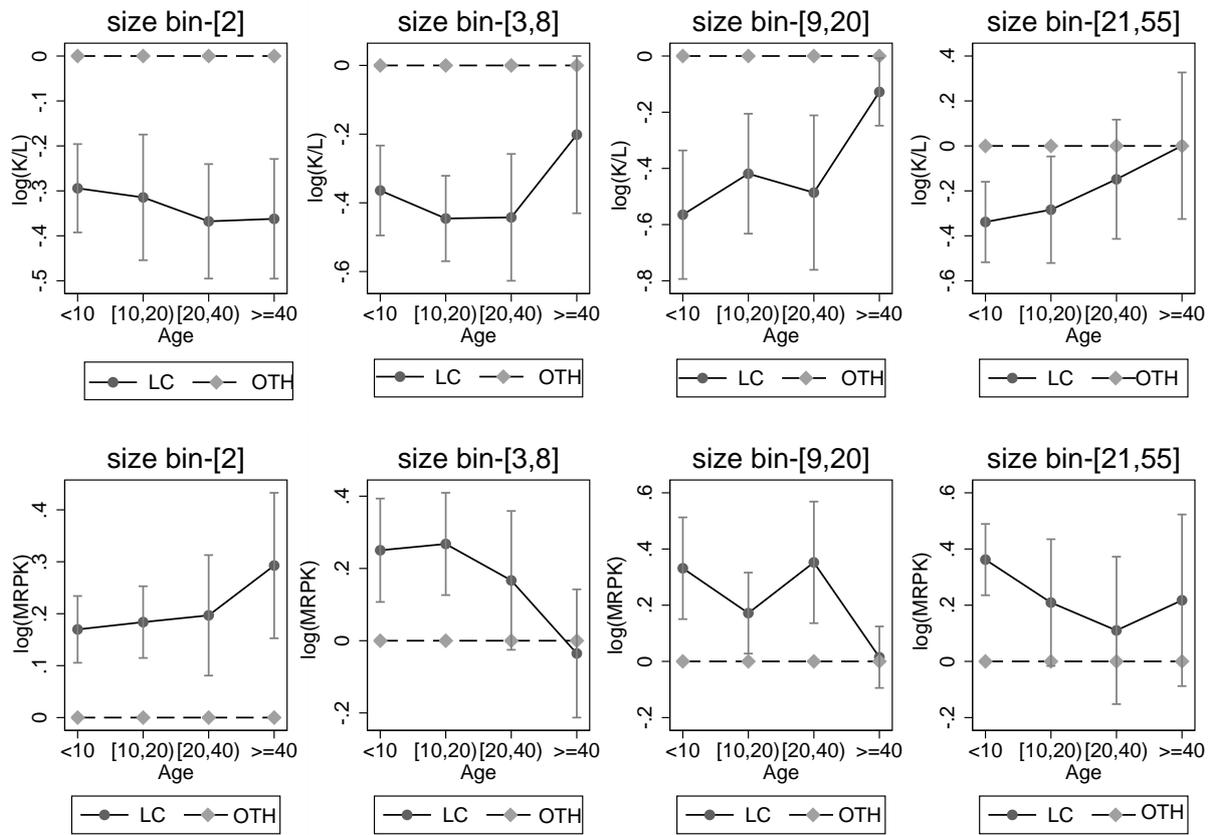
To test this hypothesis, I segregate enterprises of each size bin (same as before) into 5 different age-groups and plot the β_1 and β_2 using the regression model defined in equation 1. Figure 3 shows that the differences remain for younger and middle-aged enterprises but as they become older, their capital intensity increases and the MRPK decreases. This suggests that indeed the low-caste entrepreneurs face considerable frictions in the beginning of their life-cycle but those who survive accumulate enough capital over time. Such evidence corroborates the presence of tighter borrowing limits for the low-caste entrepreneurs. However, one has to be cautious in interpreting these results because it is plausible that the the low-caste enterprises that are born in different years are inherently different from each other and the fact that they are more capital-intensive and have lower MRPK is not related to their age. Such concerns can be ruled out only with panel dataset, which does not currently exist, so I leave this inquiry for future research.

[Hadlock and Pierce \(2010\)](#) suggest that size and age are good predictors of financial constraints. Young and small entrepreneurs are most constrained whereas large and old are least likely to be constraint. In the same spirit I also find that majority of the differences in MRPK and capital intensity are driven by small and young low-caste entrepreneurs.

Fact 3: Caste-dependent misallocation of capital

The misallocation of capital within a sector (as measured by the dispersion in the MRPK) can be decomposed into across- and within-caste components using a variance decomposition. I compute this variance decomposition for the formal sector of the economy. The across-caste

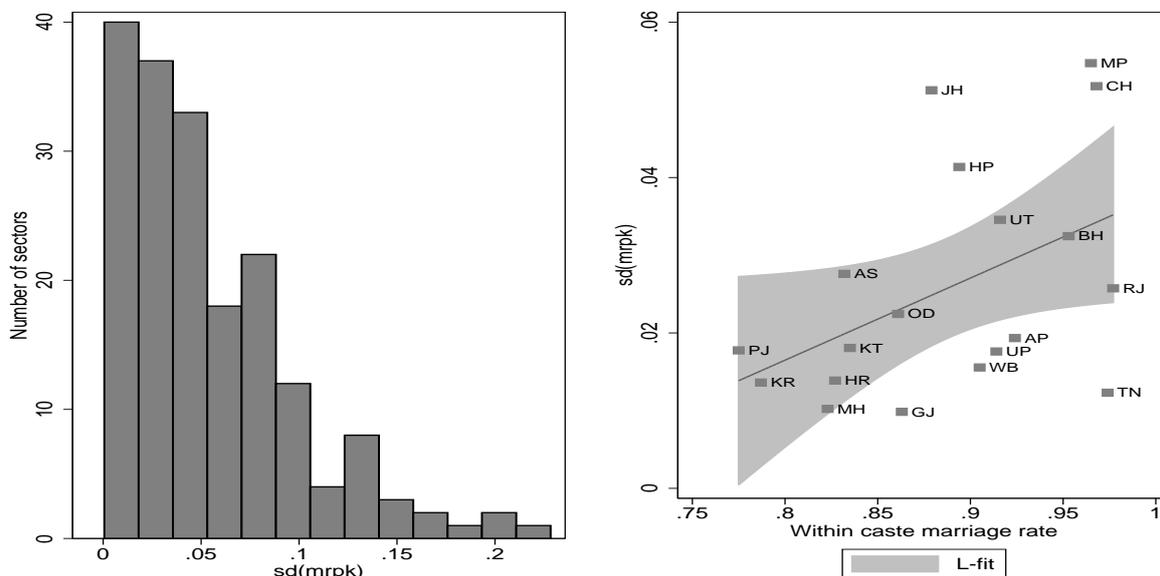
Figure 3: Capital intensity & MRPK across Age & Size: 2006



Notes: Coefficients of the low caste dummy from regressions of $\log(k/l)$ (column 1) and $\log(\text{MRPK})$ (column 2) using specification 2 and 5 in Table 3 for each age bin on the X-axis. Rows represent the employment bins.

component is heterogeneous across sectors and varies from 1 to 25% of total misallocation, see Figure 4. This shows that caste-specific distortions explain a substantial portion of the total dispersion in the MRPK and they are quantitatively important.

Figure 4: Caste-dependent misallocation of capital: MSME 2006



Notes: On the right, x-axis represents the across caste component of dispersion in $\log(\text{MRPK})$ and y-axis is number of sectors. On the left, x-axis is the within caste marriage rates for different regions in India (19 in total) and y-axis is the dispersion in the $\log(\text{MRPK})$ in each region.

Next, I aggregate the within-sector measure of caste-dependent misallocation for different regions in India where the within-sector component is weighted by the contribution of each sector in the region's GDP. The caste-dependent misallocation varies from 1 to 6% across regions. In principle, the caste-based misallocation should be higher in the regions where the caste system is more strictly enforced. In a region where the caste system is fully enforced (caste autarky), savers from the high castes cannot lend to productive but poor low-caste entrepreneurs. Meanwhile, those regions where caste is irrelevant, caste-dependent misallocation of capital would be zero because capital flows towards the most productive entrepreneurs. In order to test this hypothesis, I use within-caste marriage rates as the proxy for its strength across regions. Figure 3 shows a positive and significant correlation between the across caste component of misallocation and the within-caste marriage rates. This suggests that in regions where the caste system is more strictly enforced, the low-caste entrepreneurs face higher restrictions to capital markets, and generating more misallocation of capital.

Fact 4: The growth rate of capital for each cohort of entrepreneurs is lower for low caste

Until now, I have provided cross-sectional evidence on how capital constraints could be responsible for generating differences in the MRPK and capital-labor ratio across castes. Here, I corroborate those claims by documenting some time series evidence on capital growth over time for different cohorts of enterprises. Specifically, I use repeated cross-sections of the 2006 and 2001 MSME, and compute the growth in the capital stock for enterprises that belong to the same sector, caste and age. For example, the cohort of enterprises that enter the market in 2001 are present in the 2001 cross-section and those who survive also appear in the 2006 cross-section. I calculate the mean capital stock for these enterprises at the *caste* \times *sector* level and then compare its growth rate over time for different castes.

In order to do so, I use the regression model shown in equation 3, where dependent variable k_{scyt} is the mean capital stock for firm in sector s , caste c , year of entry y and time t . y_{scyt} is the mean output, α_t is a time fixed effect, γ_c is caste fixed effect, α_{sy} is a *sector* \times *year* – *of* – *entry* fixed effect and ε_{scyt} is the error term. I am interested in the coefficients γ_1 and γ_2 , which represent the average growth of the (mean) capital stock from 2001 to 2006 for the middle- and low-caste entrepreneurs relative to the high-caste entrepreneurs respectively.

$$k_{scyt} = \gamma_0 + \gamma_1 \mathbb{1}_{L-Caste} \times \alpha_t + \gamma_2 \mathbb{1}_{M-Caste} \times \alpha_t + \gamma_3 y_{scyt} + \alpha_t + \alpha_{sy} + \gamma_c + \varepsilon_{scyt} \quad (3)$$

The results are presented in Table 4. I include only 4 years of entry from 1998-2001,¹² although results remain unchanged for any number of cohorts. I find that the average low- and middle-caste entrepreneur experience a much slower growth of capital relative to high caste entrepreneurs while controlling for changes in output. Column 2 in Table 4 pool together all observations for the four cohorts between 1998 and 2001, whereas subsequent columns show the results for each cohort individually. For instance, column 3 shows that there is a large heterogeneity in the growth of capital across castes for the new entrants. The capital stock

¹²I can include all cohorts of firms by age and results do not change. I choose only four cohorts (1998-01) because including more increase the risk of aggravating the truncation bias (all the enterprises that are present in 2001 may not appear in 2006 cross-section because of the ceiling).

grew 0.36 log points slower for the low-caste entrepreneurs in the next 5 years whereas it is 0.55 log points slower for the middle-caste relative to the high-caste.

Table 4: Capital Growth rates for different cohorts: 2001-06

Entry year	k_{set} 1998-01	k_{set} 2001	k_{set} 2000	k_{set} 1999	k_{set} 1998
Output	0.884 (0.026)	0.963 (0.066)	0.845 (0.050)	0.872 (0.048)	0.861 (0.044)
$\alpha_t \times$ M-Caste	-0.542 (0.033)	-0.408 (0.076)	-0.538 (0.065)	-0.670 (0.066)	-0.536 (0.061)
$\alpha_t \times$ L-Caste	-0.357 (0.046)	-0.344 (0.130)	-0.275 (0.085)	-0.379 (0.085)	-0.410 (0.086)
Sector \times Entry-year FE	Yes	Yes	Yes	Yes	Yes
Caste FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Observations	2774	599	712	715	748
Adjusted R-squared	0.798	0.779	0.838	0.778	0.797

Notes: Results from the sector level regressions, equation 3. Dependent variable k_{scyt} is the mean capital stock for firm in sector s , caste c , year-of-entry y and time t . y_{scyt} is the mean output, α_t is a time fixed effect, γ_c is caste fixed effect, α_{sy} is a *sector \times year - of - entry* fixed effect. $\alpha_t \times$ M-caste and $\alpha_t \times$ L-caste is interaction of dummy variable for the year fe \times middle-caste enterprises, and year fe \times low-caste enterprises respectively. Output is the mean output at the sector-caste-entry level. The standard errors are in parentheses, clustered at entry-sector level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

There are two caveats to the results presented above. First, I assumed that the entrepreneurs of all castes have access to the same production technology and so their capital requirement are also similar. If this is not true than such differences in capital growth can be attributed to differences in production process, organization structure, business model, for-example. Second, the data only have micro and small enterprises and it could be the case that there are some enterprises that entered small in 2001 but outgrew the criteria to be classified as micro or small enterprises in 2006 and as a results were not captured by the 2006 census, biasing results downwards. This would happen because it is the high-caste entrepreneurs that grow faster and as argued earlier, they are less likely to be captured by the MSME census relative to low castes.

Until now I have document that the historically disadvantaged castes are less likely to start an enterprise. Those who manage to enter into the market are less capital-intensive and have

higher MRPK relative to high castes. Moreover, the regional variation in the strength of caste system positively correlate with the caste-specific misallocation of capital. Finally, the low- and middle-caste entrepreneurs, especially the new-entrants, experience slower growth of capital relative to the high caste. This suggests that the younger low-caste entrepreneur adjust their capital stock relatively slowly, although conditional on survival they reach the similar level of capital intensity as of high castes.

In the next section, I build a general equilibrium model where agents of different castes make occupation choice in the context of caste-specific fixed cost of entry and borrowing limits to study the macroeconomic implications of these facts. In the model, I only use two castes with corresponding population proportions: low (24%) and high (76%). All these results remain intact if I divide the population of India into two groups: low and high caste (where I merge the middle caste into the high caste), column 2 of Table 6.

5 Model

I formalize the idea of a caste-specific fixed cost of entry and borrowing limits within the framework of [Buera and Shin \(2013\)](#). The model includes financial frictions in a parsimonious way; i.e., the amount of capital that one can borrow solely depends upon its asset base. A crucial point is that the low-caste entrepreneurs with similar asset base cannot borrow as much as the high-caste entrepreneurs.

Time is discrete and there is a continuum of infinitely lived agents that are heterogeneous across productivity z , asset-base a , and caste c . At any point in time, the economy is characterized by a joint distribution of agents $G_t(a, z, c)$.

Productivity: Entrepreneurial productivity z follows a stochastic process. From one period to another, agents retain their productivity with probability ψ , and with probability $1 - \psi$ they lose their current productivity and draw their new productivity from a stationary Pareto distribution $\mu(z, \eta)$ with scale parameter η . ψ represents the persistence in the productivity process. If $\psi = 1$ then there is no uncertainty and hence productivity is the sole determinant of the agent's saving behavior and occupational choice. On the contrary, when $\psi = 0$, the

productivity process is a random walk.

Preferences: Agents' utility functions are strictly increasing, 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 following function:

$$\mathbb{E}_t \sum_{s=t}^{\infty} \rho^{s-t} \frac{c_s^{1-\gamma} - 1}{1-\gamma}. \quad (4)$$

Occupation: In each period, agents choose their occupation $o(a, z, c)$ depending upon their productivity and asset base. They can either be an entrepreneur e or work for a wage w :

$$o_t(a, z, c) \in \{e, w\}. \quad (5)$$

Technology: The entrepreneurs have access to a decreasing returns to scale production function $f(z, k, l)$:

$$f(z, k, l) = z(k^\alpha l^\beta)^{1-\nu}, \text{ where } \alpha + \beta = 1, 0 < 1 - \nu < 1. \quad (6)$$

$1 - \nu$ is the span-of-control parameter. An entrepreneur rents capital k in the financial market (more discussion follows below) and labor l to produce y units of a single good.

Entrepreneurs need to pay a per-period fixed cost κ_c which is caste-dependent. This assumption encapsulates the idea that the low-caste agents face relatively higher opportunity cost of entry; i.e., $\kappa_{hc} < \kappa_{lc}$. The presence of higher fixed costs makes entrepreneurship a relatively less profitable venture for the low-caste agents and results in low entrepreneurship rate. Moreover, it pushes up the average productivity of the low-caste entrepreneurs because only the agents with high enough productivity can enter entrepreneurship and the rest joins the labor-force.

Financial Markets: There is a perfectly competitive intermediary that receives deposits from savers and lends these funds to entrepreneurs. There is no intermediation cost; i.e., the deposit rate is equal to the borrowing cost. The rental rate of capital is $r_t + \delta$ in period t , where δ is a time invariant depreciation cost and r_t is the deposit rate. The financial markets are incomplete in a way that entrepreneurs' ability to borrow capital is proportional to their asset

base. Specifically, the capital constraints take the following form

$$k_t \leq \lambda_c a_t; \quad a_t \geq 0, \quad (7)$$

where λ_c measures the degree of credit constraints and varies from 1 to ∞ . $\lambda = 1$ represents an economy with financial autarky (no availability of credit), whereas $\lambda = \infty$ reflects perfect financial markets. In this paper, I assume that λ_c is caste dependent such that the low-caste entrepreneurs face stricter borrowing constraints than the high-caste ones, $\lambda_{hc} > \lambda_{lc}$. The lower λ_c limits the amount of capital that entrepreneurs can borrow. In equilibrium, both λ_c and κ_c affect the wealth distribution of the low caste agents making them relatively poorer on average.

Recently, financial frictions based on cash flows rather than collateral are being used in the literature, such as [Buera et al. \(2011\)](#). However, I argue that collateral-based financial constraints are more common in India as the majority of loans are based on collateral and not on cash flows; e.g., more than 84% of the loans required collateral in India in 2014 according to the world enterprise survey 2014, World Bank.¹³

Similar to [Buera and Shin \(2013\)](#), I rule out any borrowing for intertemporal consumption smoothing by assuming $a_t \geq 0$. 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.

Individual Problem: At time t , agents maximize their expected utility for a given sequence of factor prices $\{w_t, r_t\}$, their asset base a_t , productivity z_t , and productivity process as mentioned above, such that the resource constraint always binds. The value function that agents maximize is:

$$v_t(a, z) = \max_{\{a_{s+1}, c_s\}_{s=t}^{\infty}} \mathbb{E}_t \sum_{s=t}^{\infty} \rho^{s-t} \frac{c_s^{1-\gamma} - 1}{1-\gamma}, \quad (8)$$

$$s.t. \quad a_{t+1} \leq \max\{\pi_t(a, z, c; r_t, w_t), w_t\} + (1 + r_t)a_t - c_t.$$

¹³The micro-data for WES is available on: http://microdata.worldbank.org/index.php/catalog/2225/get_microdata

In this economy, the entrepreneurial choice for k and l in period t is independent of the entrepreneur's saving decision a_{t+1} . Hence, the profit maximization problem can be written as:

$$\pi_t = \max_{\{l_t, k_t\}} \left\{ z_t (k_t^\alpha l_t^\beta)^{1-\nu} - w_t l_t - (r_t + \delta)k_t - \kappa_c, \text{ s.t. } k_t \leq \lambda_c a_t \right\} \quad (9)$$

Equilibrium: At time t , given the distribution $G_t(a, c, z)$, the equilibrium of the economy is characterized by a sequence of allocations $\{o_s, c_s, a_{s+1}, k_s, l_s\}_{s=t}^\infty$, factor prices $\{w_s, r_s\}_{s=t}^\infty$, and $G_t(a, c, z)_{s=t+1}^\infty$ such that agents maximize utility, and capital, labor and goods markets clear. Appendix A.3 provides further details.

5.1 Misallocation across Castes

The main objective of this paper is to quantify the misallocation of resources across castes and its impact on aggregate TFP, capital-labor ratio and output. The literature has stressed the role of financial frictions and fixed costs on two different margins of misallocation: the extensive and the intensive.

Extensive Margin: as explained earlier, the extensive margin refers to the distorted occupation choice. In this economy, the presence of heterogeneous fixed cost κ_c makes the entry of the low-caste agents less probable than others. Moreover, the presence of borrowing constraints also distorts the entry of entrepreneurs. In equilibrium, the capital demand goes down which in turn reduces the interest rate r_t . The wage rate also decreases as the supply of labor increases. This reduces the productivity of the marginal high caste entrant.

Suppose that the low-caste agents have higher fixed cost than high-caste agents and lower λ_c . Under such circumstances, the low-caste productivity threshold $\bar{z}(a, \kappa_c, \lambda_c)$ is higher than the high-caste one, which implies higher labor-force participation and lower entrepreneurial rate for the low-caste agents. One important implication is that the average productivity of the low-caste entrepreneurs should be relatively higher than that of high castes because only the very productive low-caste agents can operate profitably. However, such a reduction in entrepreneurship means lower demand for factors of production which in turn implies lower factor prices and higher profits for incumbent entrepreneurs. This allows the entry of more

high castes who are marginally unproductive. As a result, the overall TFP of the economy goes down.

Intensive Margin: this margin refers to the dispersion in the marginal revenue product of capital (MRPK) across enterprises. Similar to the extensive margin, this paper focuses on the dispersion of the MRPK across castes. The dispersion arises because of the differences in the λ . The consumption Euler equation for constrained entrepreneurs contains Λ_{t+1} , the shadow value of capital:

$$c_t^{-\gamma} = \rho \mathbb{E}_t \{ c_{t+1}^{-\gamma} (1 + r_{t+1} + \lambda_c \Lambda_{t+1}) \},$$

$$\Lambda_{t+1} = \max[f_k(\lambda_c a_{t+1}, z_{t+1}) - (r_{t+1} + \delta), 0].$$

One should remember that under no uncertainty all agents can save out of their constraint and there is no dispersion of MRPKs in equilibrium ([Banerjee and Moll 2010](#)). In the presence of uncertainty, the saving function depends on the persistence of the productivity process ψ , and hence, there are constrained agents in equilibrium as well. In this paper I assume that agents of both castes follow the same productivity process. Under this assumption, conditional on the level of asset holding, the low-caste entrepreneurs face stricter borrowing constraints. This pushes their marginal revenue product of capital up, which generates a dispersion in the MRPK across castes.

In a general equilibrium model, the role of own-savings is crucial to evaluate the misallocation in the economy. The high ability agents save to smooth their consumption in the anticipation of a negative productivity shock. Moreover, they save in order to finance their capital requirements, as they are the ones who become entrepreneurs. Meanwhile, less productive agents choose to be workers and would like to borrow because they anticipate a positive productivity shock. Recall that I have assumed that asset-holdings are non-negative, so workers are constrained at zero. If the low caste agents are more likely to be workers, that implies that their asset distribution is also skewed towards the left.

5.2 Calibration

The calibration strategy is based on [Buera and Shin \(2013\)](#) and [Cagetti and De Nardi \(2006\)](#). The structural parameters $\alpha, \beta, \nu, \rho, \eta, \gamma$ and δ are both types both type of agents. This simplifying assumption is not innocuous and have implications for the interpretation of the results both in the empirical as well as in the theoretical part of this paper. As discussed above, difference in α and therefore in β ($\beta = 1 - \alpha$) for the low- and high-caste individuals would show up in the MRPK and and in the capital-labor ratio. In such a scenario, this would not be a case for misallocation and rather a differences in the production technology used by both castes. However, such difference in α would also change the MRPL across castes, but such differences are not encountered in the data (see Table 7). A similar argument applies to the difference in the span of control parameter η .

In principle, preference parameters such as the coefficient of relative risk aversion γ and the discount factor ρ could also differ across castes. It is not hard to believe that caste may have altered the preferences of individuals and made them more risk averse or less patient, and in turn change the saving behavior. In fact, [Mullainathan and Banerjee \(2010\)](#) discuss the endogeneity in the discount factor. In such a scenario, entrepreneurs may converge to a different steady state and across caste dispersion in the MRPK would not necessarily imply any misallocation due to caste-specific distortions. I assume that the preferences of individuals are same across castes. I choose $\alpha = 0.33$, $\beta = 1 - \alpha$, $\delta = 0.06$ and the coefficient of relative risk-aversion $\gamma = 1.5$, which are standard in the literature, [Cagetti and De Nardi \(2006\)](#). The discount factor is set to $\rho = 0.81$ to match the annual interest rate of 6%.¹⁴

Given the parameters α, β, γ and δ , the model is solved to match certain moments of the Indian data. The span-of-control parameter $1 - \nu$ and the tail parameter of the productivity distribution η are fixed such that the earning share (occupational income) of the top 10% of the population and the employment share of the top 5% of enterprises by size are same in the data and in the model. [Chancel and Piketty \(2017\)](#) document that the top 10% of the population takes the 45% of the national income in India in 2010 and the top 5% of the enterprises provide

¹⁴The annual real interest rate in India varies from 2% to 8.34 % between 1999 to 2010. I take the average, which is 6%

employment to the 49% of the total labor-force in the manufacturing sector in 2005.¹⁵

To discipline the persistence of the productivity process, I match the exit rate of the enterprises in the manufacturing sector. [Hsieh and Klenow \(2014\)](#) document the exit rate in the manufacturing sector of India to be between 5-10 % for different age groups. I use the upper bound of the exit rate; i.e., 10% and set $\psi = 0.890$. I use these statistics for the manufacturing sector due to the lack of employment distribution and the exit rate for all the sectors in the Indian economy.

The parameters ψ and η guide the persistence of the productivity process and the dispersion in the productivity distribution respectively. It is quite plausible that the underlying productivity distribution are different for the low- and high-caste individuals. [Fehr and Hoff \(2011\)](#) and [Hoff and Pandey \(2006\)](#) argue that caste affects cognitive task performance and responses to economic opportunities by young boys in village India. Due to lack of data on exit rates, I can not calibrate these parameters for each caste. Moreover, the whole premise of the paper is that the low castes are not less productive by birth and it is the caste-specific distortions that obstruct their performance, in this case establishment size and performance. Therefore, observed differences in productivity should be attributed to caste-specific distortions and not to innate differences among them. In the baseline calibration of the model, I assume ψ and η to be common across castes but discuss the implications of these assumptions in detail in the next section.

For other parameters that differ across castes, I match the entrepreneurial rates for the low- and high-caste entrepreneurs, overall credit-GDP ratio and its difference across castes in the MSME sector. In principle, one should calibrate λ_c by targeting the credit-GDP ratio for each caste. I am not able to do this due to the absence of data on credit for the whole universe of firms in the MSME dataset. In order to overcome this issue, I match the overall credit-GDP ratio which is 0.42 for India.¹⁶ Additionally, I compute the difference in the credit-GDP ratio

¹⁵I compute the firm size distribution using Annual Survey of Industries(ASI), which covers registered manufacturing plants and combine it with the National Sample Survey(NSS) for the unorganized sector (plants with less than 10 workers or 20 workers if without power). [Garcia-Santana and Pijoan-Mas \(2014\)](#) use the same dataset to compute firm size distribution in India)

¹⁶The domestic credit to private sector in India varies between 30-50% from 2000-10, World-Bank database. I take the average, which is 42%. In the MSME dataset, the credit-gdp ratios for the high- and low-caste are 7.1 and 3.9% respectively.

Table 5: Structural Parameters of the model

Exogenous parameters		
δ	0.06	Cagetti and De Nardi (2006)
α	0.33	Cagetti and De Nardi (2006)
β	0.67	$1 - \alpha$
γ	1.5	Cagetti and De Nardi (2006)
Calibrated parameters		
	Data	Model
Interest rate		6% ($\rho = 0.81$)
Establishment Exit rate	10%	10% ($\psi = 0.890$)
Top 10 % income share	45%	44% ($v = .22$ and $\eta = 4.5$)
Top 5 % employment share	49%	48% ($v = .22$ and $\eta = 4.5$)
Entrepreneurial rate-OTH	87%	87% ($\kappa_{hc} = 0.50$)
Entrepreneurial rate-LC	13%	13% ($\kappa_{lc} = 0.93$)
Credit/Value-added		
Overall	0.42	0.42 ($\lambda_{hc} = 1.66$ and $\lambda_{lc} = 1.29$)
Difference across castes	85%	85% ($\lambda_{hc} = 1.66$ and $\lambda_{lc} = 1.29$)

Notes: All statistics for data part are calculated by using MSME census 2006 except that entrepreneurial rate is computed with Economic census 2005, top 10% income share comes from Chancel and Piketty (2017) (In their paper, this income share varies from 45-55%) and top 5% employment share comes from the NSS-ASI dataset, Garcia-Santana and Pijoan-Mas (2014).

between the high- and low-caste over small and medium firms in the model, defined as bottom 99% of the firms in the capital stock distribution, and set it equal to its counterpart in the MSME dataset.

For the fixed costs parameters, I could also match the percentage of employment provided by each caste entrepreneurs. This would imply even higher fixed costs in the model and increase the losses at the extensive margin. Therefore, I use the entrepreneurship rates to discipline fixed costs in the benchmark economy and consider my extensive margin losses to be a lower bound.

It is important to note that λ_c has an effect on the extensive margin (entrepreneurial rate) and the intensive margin (credit-GDP ratio) whereas κ_c only affects the extensive margin. Therefore, both parameters are jointly determined in equilibrium. Moreover, in the presence of financial frictions, η and $1 - v$ also influence the entrepreneurial rate and the dispersion in the capital-labor ratio (η and $1 - v$ have no influence in the limiting case i.e. $\lambda_c \rightarrow \infty$). Given these six moments of the data, one can jointly measure all six (η , $1 - v$, λ_{hc} , λ_{lc} , κ_{hc} and κ_{lc}) parameters. Table 5 lists all the exogenous and the calibrated parameters.

5.3 Results in the Stationary Equilibrium

Under the calibration as shown in Table 6 below, the model implies that the low-caste entrepreneurs face 86% higher fixed costs and 22% lower borrowing limit as compared to their high-caste counterparts. In the data, as discussed earlier, I observe enterprises below a certain threshold of investment. I look at the complete distribution of enterprises in 2005 and find that this threshold kicks in at around the 99th percentile of the capital stock distribution. In order to compare the results in the model and in data, I compute all statistics for MSME's (column 2) and all firms (column 3) in the model.

The low-caste entrepreneurs are 14% less capital intensive and have 14% higher MRPK relative to high castes if I only consider the MSME's in the model. However, these differences are 3 percentage points lower if I compare all the enterprises, panel A. column 3 of Table 6. This implies that large enterprises are less constrained in the model and it is consistent with the findings of section 4, where I document that differences in the MRPK and capital-intensity across castes decline with firm size.

In comparison to the data (see panel A of Table 6), the model captures around 60% and 80% of the differences in the capital intensity and MRPK, respectively. Meanwhile, size of the low-caste entrepreneurs is 3% smaller relative to high castes in terms of value-added and 16% in terms of capital stock. In the model, there are two opposing forces that affects the size of low castes relative to high castes. First, the fixed cost raises the threshold productivity and thus implies higher size. However, a stricter borrowing constraint restricts size because it inhibits the ability to borrow and also encourages wealthy but unproductive agents to enter. In equilibrium, overall size is lower for the low-caste entrepreneurs although these differences are smaller than what I find in the data. This suggests that there are other frictions such as labor market frictions, human capital differences, among others, that prevent low castes from increasing their capital intensity.

In terms of productivity, TFPR and profitability are 3.5% and 4.1% higher relative to the high-caste entrepreneurs in the model respectively. The TFPR differences are much lower in the model (3.5%) than in the data (10%). This implies that, in the data, the selection effect is much stronger than in the model. The effect of weak selection in the model can also be

Table 6: A. Comparison of Empirical results with the Model

A. Differences among low and high caste enterprises in benchmark economy			
	Data (MSME)	Model (MSME)	Model (ALL-Firms)
k/l	-25%	-14%	-11%
mrpk	16%	14%	11%
tfpr	10%	3.5%	0.4%
Profitability	5%	4.1%	3.1%
sd(mrpk)	-13%	3%	2%
value-added	-17%	-1%	-3%
capital	-33%	-13%	-16%
employees	-7%	-1%	-3%
B. Gains in the counterfactual relative to benchmark economy			
<i>Low caste entrepreneurs</i>			
values-added			4%
employees			0.5%
capital			15%
k/l			14%
mrpk			-10%
lp			5%
<i>Overall Economy</i>			
GDP			6%
k/l			8%
TFP			3%
credit/GDP			9%
Interest rate			13%
Entrepreneurs			-4%
tfpr			4%

Notes: All statistics for data are calculated by using MSME census 2006. Differences in all the variables between low and high caste entrepreneurs are conditional means that are computed while controlling for sector, regional, gender, religion and human capital differences. sd(mrpk) which represents within sector difference in dispersion of mrpk. All statistics for model in panel A are computed with benchmark calibration. Panel B. computes the (mean) change in the variable in the counterfactual economy relative to the benchmark economy.

seen in the measure of within-caste dispersion in the MRPK which is higher for the low-caste entrepreneurs relative to the high-caste entrepreneurs.

In terms of credit, the ratio of credit-to-total-assets is 58% lower whereas the ratio of credit-to-value-added is 68% lower relative to the high-caste entrepreneurs. The former is the manifestation of higher borrowing limits for low-caste entrepreneurs. The differences in the latter are even greater because of the substitution of capital with labor in the enterprise's profit optimization. The low-caste entrepreneurs adjust their factor mix, tilting more towards labor as evident from lower capital intensity, to reach closer to their optimal output (although, they never reach this level). Such adjustment implies greater differences in the usage of credit to produce one unit of output (credit/value-added) between the low- and high-caste entrepreneurs.

However, caste difference in leverage are over-predicted by the model. In the data, less than 10% of firms have access to the financial markets while in the model most of the firms do have access to the financial markets. This means that the average firm with positive credit is much smaller in the model than in the data. Given the structure of financial frictions, which constrain small firms relatively more, suppress the average leverage of low caste relative to others. A model with financial frictions that also has a fixed component would more closely match the leverage ratio differences. These fixed costs that enable entrepreneurs to get access to financial markets would be higher for low-caste agents as only 8% (less than their entrepreneurship rate, 13%) of financially active firms belong to the low-caste agents. This would increase the misallocation in the benchmark economy. Hence, I argue that my estimates are lower bounds of caste-dependent misallocation of capital.

5.4 Discussion on Parameterization

The persistence of the productivity shocks ψ has two important implications for the economy as discussed in [Buera et al. \(2011\)](#), [Moll \(2014\)](#) and [Buera and Shin \(2013\)](#). First, it determines the amount of individuals that need to redraw their productivity. Second, it determines the importance of the self-financing channel in overcoming the capital constraints in the economy. If the profitability is persistent enough then agents can accumulate enough assets to be unconstrained in the steady state. Meanwhile, if the productivity shock is transitory (low ψ)

then self-financing is not powerful enough to overcome capital misallocation due to capital constraints and therefore TFP losses are also large in the steady state.

Now imagine an economy where both castes face similar borrowing limits λ but ψ is higher for the low-caste entrepreneurs relative to high-caste entrepreneurs. Similar to the benchmark calibration, the low-caste entrepreneurs would be more constrained, have higher MRPK and more capital misallocation. Meanwhile, contrary to the baseline calibration, the low caste enterprises would have higher exit rate and both the credit to asset ratio and the credit to value-added ratio would be the same across castes. However, as pointed out before, both of these ratios are lower for low caste entrepreneurs in the data, which can be interpreted as corroborative evidence in the support of my baseline calibration.

The dispersion in the productivity process is guided by η in the benchmark calibration. Imagine an economy with perfect credit benchmark ($\lambda \rightarrow \infty$), then tail parameter η solely guides heterogeneity in productivity. In such circumstances, the higher the value of η means lower dispersion and vice versa.

A larger dispersion in the talent distribution causes more misallocation of talent and capital in the stationary equilibrium under the presence of financial frictions. If the low-caste entrepreneurs have more dispersed distribution than within these enterprises misallocation would be higher. However, the data suggest dispersion in the MRPK is higher for the high-caste entrepreneurs (see panel A of Table 6). Moreover, differences in η cannot generate differences in the credit-to-asset ratio and the credit-to-value added ratio at the enterprise level. Therefore, such differences cannot explain the misallocation across caste.

5.5 Counterfactual Analysis

In this section, I analyze the effects of eradicating caste-specific distortions in the economy on overall TFP, capital-labor ratio and output. Moreover, I also document the changes observed in the low-caste enterprises. In doing so, the fixed cost for low caste agents κ_{lc} is reduced to the level of the fixed cost for high-caste agents κ_{hc} and the degree of borrowing constraints for the low-caste entrepreneurs λ_{lc} is equalized to the degree of borrowing constraints for the high-caste entrepreneurs λ_{hc} in the benchmark economy. According to the model, in such an

economy, the overall capital-labor ratio and GDP increase by 8% and 6% respectively (panel B. Table 6).

These gains come from two main sources: first, the reallocation of capital from less productive high-caste entrepreneurs to more productive low-caste entrepreneurs increases the efficiency of the economy and therefore, the output and capital intensity as well. These gains are observed at the intensive margin. In such an economy, there is no dispersion in the MRPK across castes. Second, the reduction in the fixed cost and increase in the borrowing limits induce entry of more low-caste entrepreneurs. The share of the low-caste enterprises increases from 13% in the benchmark economy to 24% in the counterfactual economy. Moreover, due to lower borrowing constraints, demand for capital increases. This implies a 13% higher interest rate in the counterfactual economy. Such an increase in the cost of capital pushes less productive high-caste agents out of the market and reallocate the resources to more productive low-caste entrepreneurs. As a consequence, the overall TFP in the economy increases by 2.54%.

The size of the low-caste enterprises grows by 4% and 15% in terms of output and capital stock respectively. The capital intensity also increases by 14%. Such changes at the enterprise level could potentially have major consequences for the welfare of the low-caste individuals. In the MSME census 2006, I find that around 70% of the employees for any enterprise belongs to the same caste as the caste of the entrepreneur. This could be efficient or inefficient depending upon the kinds of frictions present in the labor market of India. In such a scenario, if lower financial frictions mean larger scale of operation for the low-caste entrepreneurs then this would benefit disproportionately the labor of the low-caste individuals. Moreover, such changes would lead to higher wages (due to increased labor productivity, 4% increase relative to the benchmark economy) and more movement of low-caste from agricultural sector to manufacturing and services. Therefore, improvements in the financial markets would have implications for labor market outcomes as well.

Finally, I perform two more counterfactual exercises to highlight the importance of misallocation at the extensive and intensive margins and disentangle the gains from two sources. First, I equalize the MRPK across castes keeping constant the number of entrepreneurs and productivity distribution. This makes the across-caste misallocation of capital equal to zero. This

allows the low-caste entrepreneurs to increase their capital intensity and as a result their size and labor productivity improve. The reallocation of capital from the unproductive high-caste entrepreneur towards low castes raises the TFP of the economy by 1.03%.

Next, I also allow the entry of productive low-caste entrepreneurs who could not enter before because of higher fixed cost or smaller borrowing limits. The productive but poor low-caste entrepreneurs would enter and unproductive high-caste entrepreneurs would exit. This improves the average productivity of entrepreneurs by 4%. Moreover, the number of entrepreneurs decreases by 4%. Lower borrowing constraints create more demand for capital, increasing the price of capital. This further improves the selection of entrepreneurs. As a result, the overall TFP of the economy improves by 1.51%. The TFP gains from removing misallocation at the extensive margin represents 60% of the total gains.

[Hsieh and Klenow \(2009\)](#) argue that if capital and labor were efficiently allocated in India then the TFP would be around 50% higher in the manufacturing sector. Therefore, I conclude that caste specific distortions in the capital markets are important and need special attention from policy makers but they are not the whole story as far as misallocation in India is concerned. Potentially, there are many other firm-level distortions present in the Indian economy that drag productivity growth.

6 Conclusion

In this paper I have established a link between a type of ethnic heterogeneity and the misallocation of resources, particularly capital and talent. As a source of such fractionalization, I have used the caste system in India, which categorizes people into different occupations at birth. I define three different caste groups, i.e., low castes (historically disadvantaged castes placed at the bottom of the hierarchy), middle castes (placed in between high and low caste) and high castes (placed at the top of the hierarchy). Historically, the low- and middle-caste agents were supposed to do menial activities and were barred from entrepreneurship. In the modern economy, it is quite plausible that the low- and middle-caste individuals are still facing considerable distortions that prevent their entry into entrepreneurship. Indeed, the data suggest these indi-

viduals are between 20% and 60% less likely to enter into entrepreneurship than the high-caste individuals, respectively.

Moreover, because the low- and middle-caste individuals are not the traditional capitalists (while the high-caste individuals are), they may lack access to modern capital markets. Indeed, the data show that the low- and middle-caste entrepreneurs are less capital-intensive and have marginal revenue product of capital relative to the high-caste entrepreneurs respectively. Such dispersion in the MRPK, which is attributed to the misallocation of capital at the intensive margin, results into a lower capital intensity and output in the economy. Further, this paper builds a general equilibrium model where agents, who differ in their productivity, asset holdings and caste, choose to become either entrepreneurs or workers. The low castes face higher fixed costs and tighter borrowing limits relative to high castes. In the benchmark economy, the model captures the majority of the differences in the MRPK and capital intensity across castes. In the counterfactual analysis, where low castes face similar fixed costs and borrowing limits as high castes, the overall capital-labor ratio and output increase by 8% and 6% respectively. Due to improved resource allocation, overall TFP improves by 2.54%.

The causal identification of the capital constraints is left for the future research. One needs to have a panel dataset with caste identifiers and an exogenous change in the credit environment in order to undertake such an endeavor. Furthermore, quantifying the aggregate effects of caste-specific labor and product market distortions is a promising research avenue.

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A Appendix

A.1 Figures and Tables

Figure 5: Caste-System in India

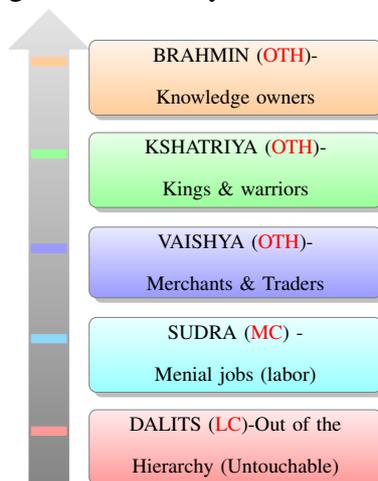


Table 7: Caste difference in MSME 2006

	M-caste	L-caste	Sector-FE 4-digit	Sector-FE 5-digit	Region-FE	Controls	Obs. (Millions)	Adj. R-squared
k/l	-0.194 (0.025)	-0.342 (0.046)	No	Yes	Yes	Yes	1.3	0.533
mrpk	0.095 (0.025)	0.229 (0.044)	No	Yes	Yes	Yes	1.3	0.463
mrpl	-0.039 (0.036)	0.036 (0.075)	Yes	No	Yes	Yes	1.3	0.239
mrpl	-0.024 (0.037)	0.060 (0.076)	No	Yes	Yes	Yes	1.3	0.251
tfpr	0.006 (0.028)	0.102 (0.058)	Yes	No	Yes	Yes	1.3	0.363
tfpr	0.013 (0.029)	0.108 (0.059)	No	Yes	Yes	Yes	1.3	0.371
profitability	0.030 (0.024)	0.086 (0.038)	Yes	No	Yes	Yes	1.3	0.464
profitability	0.035 (0.026)	0.092 (0.040)	No	Yes	Yes	Yes	1.3	0.471

Notes: Results from the enterprise level regression using equation 1. M-caste is the dummy variable for the middle-caste enterprises. L-caste is the dummy variable for the low-caste enterprises. Dependent variables are shown in the first column: k/l is capital intensity and $mrpk$ is marginal revenue product of capital. TFPR is total factor productivity revenue, TFP is physical productivity and profitability is the ratio of profits to value-added. All dependent variables are in logs except for profitability. I use a IHS transformation of the profitability as suggested in Bellemare et al. (2013). The vector of controls, Γ_i , that includes region, gender and religion FE, enterprise-level wage, number of own-caste employees, proxy for human capital (average years of schooling), average land holdings and volatility of growth rate of value-added at caste-sector-region level. There are 211 sectors at 4-digit and 6000 products at 5-digit classification. Table 7 in Appendix provides results for sector-FE at 5-digit classification (611 in total). The standard errors are in parentheses, clustered at caste-region level.

Table 8: Comparison of Revenue & Physical products of Inputs: 2006

	mrpk	mrpl	tfpr	mpk	mpl	tfp
M-CASTE	0.002 (0.056)	-0.071 (0.059)	0.037 (0.054)	0.233 (0.083)	0.158 (0.088)	0.262 (0.079)
L-CASTE	0.153 (0.119)	0.045 (0.170)	0.162 (0.139)	0.402 (0.200)	0.316 (0.277)	0.420 (0.233)
Product FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Set of controls	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	266180	262220	261806	266146	262187	261773
Adj. R	0.223	0.282	0.157	0.256	0.288	0.306

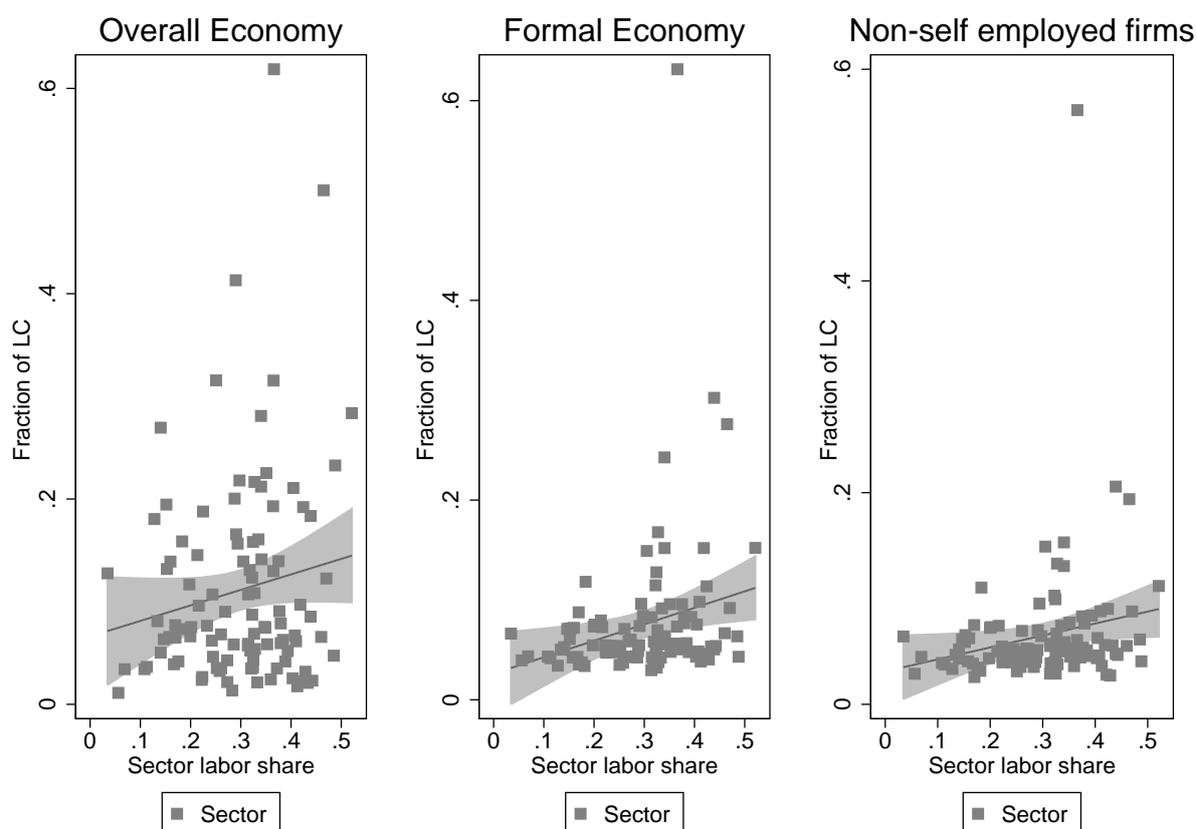
Notes: Results from the enterprise level regression. Results from the enterprise level regression using equation 1. Dependent variables are in logs and shown in column headings. mrpk, mrpl represent marginal revenue product of capital and labor respectively, whereas, mpk and mpl are physical marginal products. TFPR and TFP are revenue and quantity based measure of productivity. M-caste is the dummy variable for the middle-caste enterprises. L-caste is the dummy variable for the low-caste enterprises. The vector of controls, Γ_i , that includes region, gender and religion FE, enterprise-level wage, number of own-caste employees, proxy for human capital (average years of schooling), average land holdings and volatility of growth rate of value-added at caste-sector-region level. The standard errors are in parentheses, clustered at caste-region level.

Table 9: Caste-mix of workers: 2006

CASTE	All			Formal-Sector			Informal-Sector		
	LC	MC	OTH	LC	MC	OTH	LC	MC	OTH
LC	0.72	0.14	0.14	0.39	0.22	0.39	0.75	0.14	0.11
MC	0.07	0.82	0.11	0.14	0.63	0.24	0.07	0.85	0.09
OTH	0.10	0.19	0.71	0.15	0.21	0.63	0.08	0.17	0.74

Notes: The rows represent the entrepreneur's caste and columns represent workers' caste in different sectors. Each cell in the table represents the proportion of own-caste workers in MSME 2006 census.

Figure 6: Fraction of LC firms across sectors: 2006



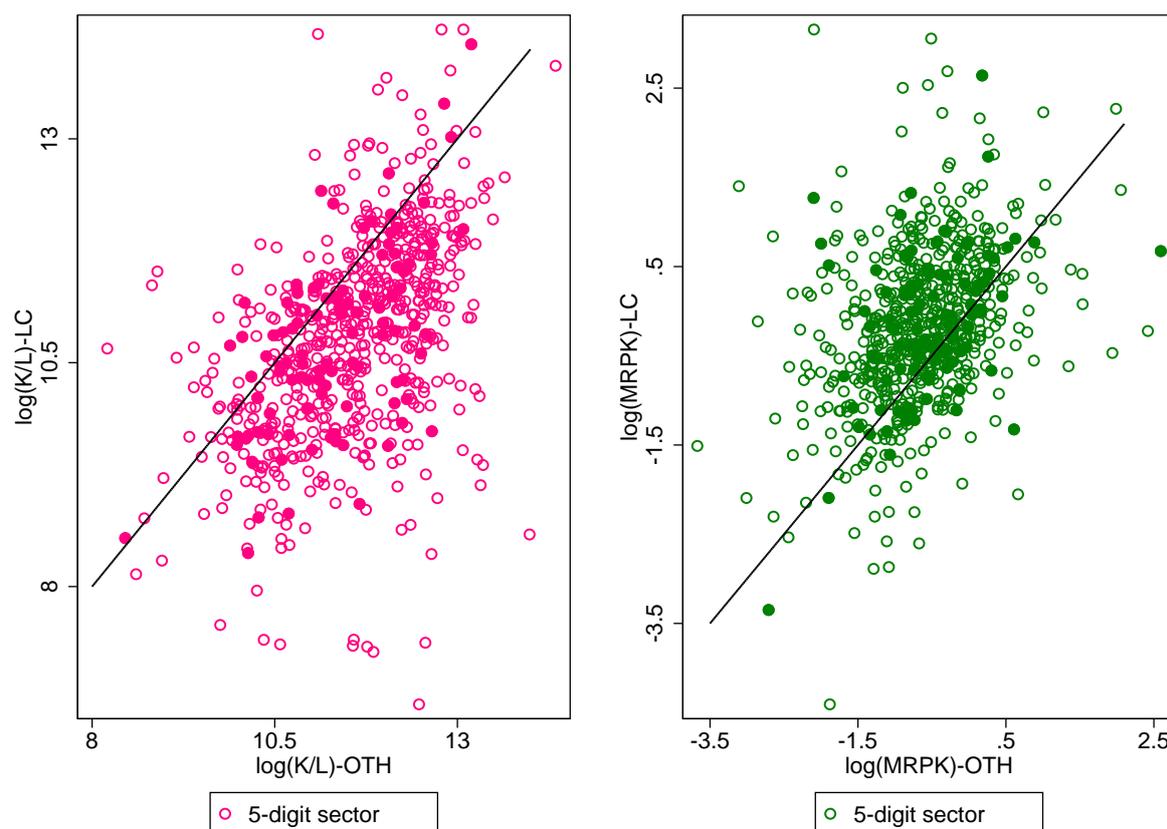
Note: The Y-axis and X-axis represent fraction of low castes in a sector and sectoral labor share respectively. The sectoral labor share is measured with NBER statistics on manufacturing sector in U.S. Each square correspond to a 4-digit sector (101 in total). From left to right, first plot represents the whole economy, second plot only includes formal firms (formal sector) and third plot is for non-self employed (firms with more than one employee) formal firms.

A.2 Data

Data Description

The MSME census is based on MSME sector which is defined by the Micro, Small and Medium Enterprise Development (MSMED) act of 2006, spans the non-agricultural enterprises of the economy that are below a certain threshold of size (size in terms of original value of investment in plant of machinery). The investment limit for enterprises engaged in the manufacturing or production of goods is Indian rupees (INR) 100 million whereas for those providing or rendering in services is INR 50 million. According to the 4th MSME census of India 2006, the MSME sector accounts for 45% of the manufacturing output and 40% of the total exports of

Figure 7: Capital intensity & MRPK across sectors: 2006



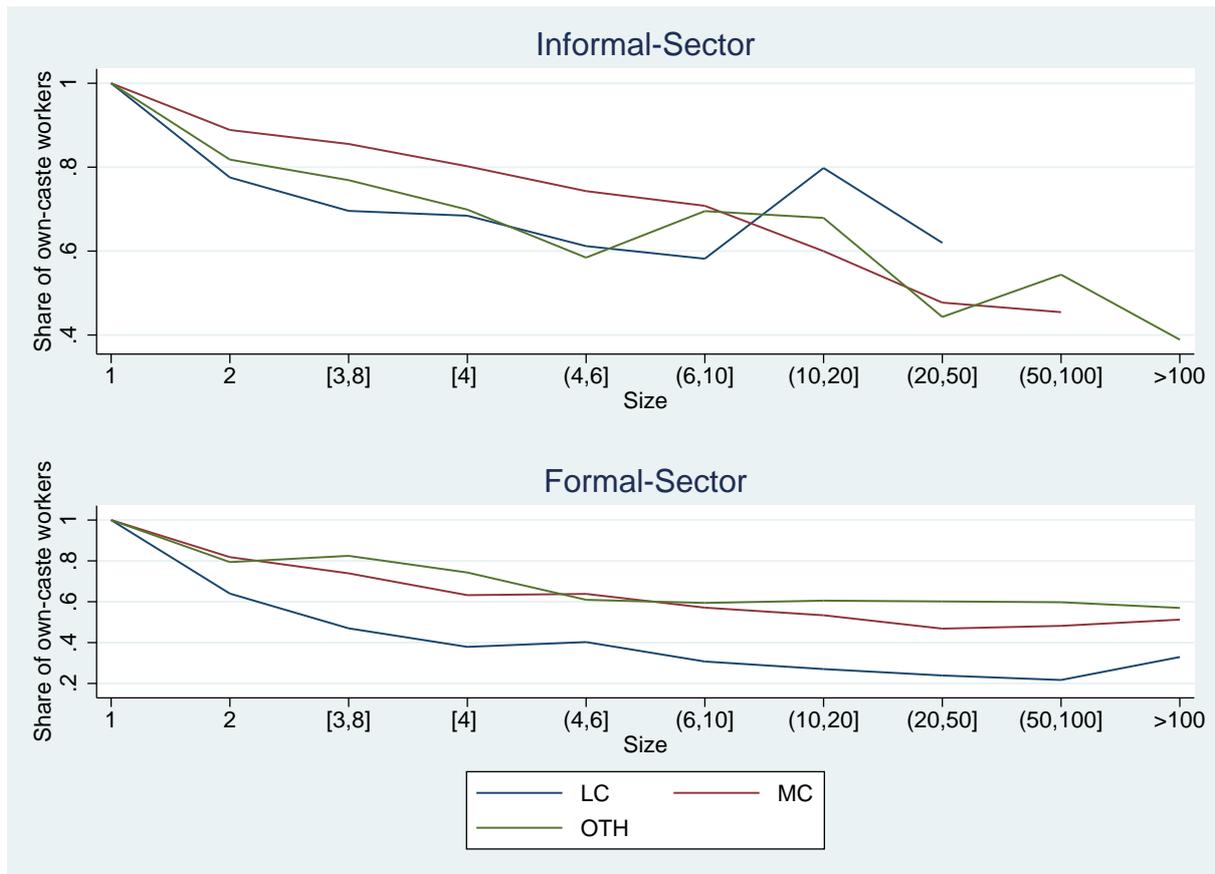
Notes: The capital-labor ratio and $\log(\text{MRPK})$ are calculated by using MSME census 2006. Each circle represents a 5 digit sector (633 in total). The dots represent sectors such as food products and beverages (NIC-15), tanning and dressing of leather; manufacture of luggage, handbags, saddlery, harness and footwear, apparels or furniture (NIC-18,19). Sampling weights are applied.

the country.¹⁷ The 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 that employ 16.62 % and 83.38 % of the workforce respectively. Overall, 29 % of them are manufacturing and 71 % are service enterprises and provide employment to 51% and 49 % of the total labor force (in the MSME sector) respectively. The Scheduled Castes and Scheduled Tribes (LC), OBC's (MC) and Others (OTH) own and operate 2.9 (11 %), 10.4 (40 %) and 11.4 (44 %) million MSMEs.

Before 2006, the MSME sector was known as SSI sector (with exclusion of medium sized firms). *The SSI sector* comprises of small scale industrial undertakings (SSIs) and small scale service and business (industry related) enterprises (SSSBs). It spans the non-agricultural

¹⁷These statistics are mentioned in MSME Annual report 2010-11 (Page 211), <https://msme.gov.in/relatedlinks/annual-report-ministry-micro-small-and-medium-enterprises>

Figure 8: Share of own-caste workers: 2006



Note: The Y-axis and X-axis represent share of own-caste workers for low caste ('LC'), middle caste ('MC') and others ('OTH'), and employment size. Top panel is for informal sector and bottom represents formal sector.

enterprises of the economy that are below a certain threshold of size (size in terms of original value of investment in plant of machinery). The ceiling was Indian rupees (INR) 10 million in 2001. There are over 4.4 million (42.26%) SSIs in the total SSI sector and the remaining 6.1 million (57.74%) were SSSBEs. The low, middle and high caste owns and operate 1.5, 4.3 and 4.3 million enterprises respectively. Within this sector, there are registered and unregistered enterprises. The registered sector accounts for 1.3 million enterprises whereas 9.1 million are present in unregistered sector.

The SSI dataset contains a census of registered SSI 13,48,451 units and a survey of 1,67,665 enterprises in the unregistered sector. The dataset includes 1.5 million observations and provides the geographical information, industry classification, balance sheet variables and the caste of the owner. The Summary statistics are available in the panel B of the Table 10. For all regressions that follows, the variables are winsorized as 1 and 99 percentile.

Unlike ASI and Prowess datasets, the economic census and the MSME datasets are able to capture small enterprises that are more likely to face financial constraints. Such effects may go unnoticed in datasets with predominantly large enterprises. Meanwhile, in the absence of large enterprises, this dataset may also upward bias the effect of caste differences. It could be that, in the overall economy, the share of such constrained enterprises is minuscule and hence caste specific frictions do not matter. I take into account such concerns while discussing the empirical results and calibration strategy and try to minimize such biases.

Table 10: Summary Statistics of the Data by Caste groups

	OTH		MC		LC		Total
	All	%	All	%	All	%	
A. Economic census 2005							
Enterprises (million)	13.3	44%	12.8	43%	4	13%	30
Employees (million)	32	50%	25	39%	7	11%	64
Employees (mean)	2.4	-	2.0	-	1.8	-	2.13
B. SSI Census 2001							
Enterprises (000s)	744	49%	592	39%	174	12%	1510
Employees (000s)	3914	62%	1972	31%	448	6%	6334
Employees (mean)	5.3	-	3.3	-	2.6	-	4.19
Age(mean)	12	-	11	-	11	-	12
Enterprise w. credit (000s)	152	55%	100	36%	26	9%	278
Repayment delays (000s)	16	46%	14	40%	5	14%	35
C. MSME Census 2006							
Enterprises (000s)	766	49%	623	40%	165	11%	1554
Employees (000s)	5618	66%	2427	28%	519	6%	8564
Employees (mean)	7.3	-	3.9	-	3.1	-	5.51
Age(mean)	12	-	11	-	11	-	12
Enterprise w. credit (000s)	102	54%	68	36%	18	10%	188
Repayment delays (000s)	11	55%	7	35%	2	10%	20

Notes: Summary statistics for all establishments are my calculations based on Economic census 2005 (Panel A), SSI census 2001 (Panel B) and MSME census 2006 (Panel C). No sampling multipliers are applied. Employees is total employment for each caste. Age is mean value for each group. Enterprise w. credit represents total number of enterprises for each group that are connected to any institution of external finance. Repayment delays represents a total number of enterprises that have delayed a payment of principal or interest in the last 12 months. Percentages indicate percent of enterprises in a group w.r.t to all enterprises.

Winsorization

The financial variable such as market value of fixed assets, gross value-added, total wage-bill, employment, amount of loan-outstanding, gross output, total cost of variable inputs and net-

worth are winsorized at 1 and 99th percentile for each caste. Furthermore, the variables used in regressions such as capital-intensity, MRPK, MRPL, leverage, profitability, TFPR and TFP are winsorized at 1 and 99th percentile for each caste.

A.3 Equilibrium definition

Equilibrium: At time t , given the distribution $G_t(a, c, z)$, the equilibrium of the economy is characterized by a sequence of allocations $\{o_s, c_s, a_{s+1}, k_s, l_s\}_{s=t}^{\infty}$, factor prices $\{w_s, r_s\}_{s=t}^{\infty}$, and $G_t(a, c, z)_{s=t+1}^{\infty}$ such that

- $\{o_s, c_s, a_{s+1}, k_s, l_s\}_{s=t}^{\infty}$ solves the individual problem in equations (7) and (8) for given factor prices $\{w_s, r_s\}_{s=t}^{\infty}$.
- Capital, Labor and Goods markets clear in each period .

$$\int_{o_s(a,z,c)=e} k_s dG_s(a, z, c) - \int a dG_s(a, z, c) = 0,$$

$$\int_{o_s(a,z,c)=e} l_s dG_s(a, c, z) - \int_{o_s(a,z,c)=w} dG_s(a, c, z) = 0,$$

$$\int_{o_s(a,z,c)=e} [z_s(k_s^\alpha l_s^\beta)^{1-\nu} - \kappa_c] dG_s(a, c, z) = \int c_s dG_s(a, c, z) + \delta K.$$

- Given the policy function a_{s+1} and productivity shocks matrix T , one can compute the transition matrix π_s . The wealth distribution next period is:

$$G_{s+1} = H(\pi_s, G_s).$$