How Does Caste Affect Entrepreneurship? Birth versus Worth

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Abstract

I investigate the relative importance of the caste system in explaining resource misallocation in India and quantify its impact on aggregate productivity. I document three main stylized facts. First, firms of historically disadvantaged castes have a higher average revenue product of capital, $arpk$, relative to firms owned by high castes, whereas no significant differences in the average revenue product of labor, $arpl$, exist. Second, across-caste dispersion in $arpk$ is primarily driven by small and young firms. Third, the majority of this dispersion is concentrated in financially underdeveloped regions in India. In a quantitative model of entrepreneurship, I find that the majority of across-caste dispersion in $arpk$ is explained by differences in access to credit and that such asymmetries reduce aggregate total factor productivity by 6% to 10%.

Keywords: Misallocation, Caste System, Financial Constraints

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The caste system doesn't just explain the lack of liberty in India. It also helps explain the country's poverty. The fact that people are locked into occupations by their inherited status puts a huge impediment in the way of social mobility and innovation. . . . Even while India has been a democracy since . . . , the dominance of caste and the gamut of restrictive, divisive, and hierarchical norms have persisted . . . . ***Talent and ability widely misallocated, wasted. Not only liberty but economic efficiency*** *was sacrificed at the altar of India's cage of norms. (Acemoglu and Robinson, 2019)*

1 Introduction

A large body of literature has argued that the misallocation of resources explains a substantial fraction of cross-country differences in aggregate productivity (see, e.g., Banerjee and Duflo 2005, Restuccia and Rogerson 2008, Guner et al. 2008, and Hsieh and Klenow 2009).[1] A number of market-oriented distortions, such as financial frictions, labor market regulation and size-dependent policies, among others, have been proposed as being responsible for resource misallocation. However, we lack systematic evidence about the quantitative importance of informal institutions, which profoundly shape individuals' economic outcomes in developing countries, in generating aggregate misallocation.

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

I use firm-level data to provide novel empirical evidence that is consistent with the presence of high levels of *caste-driven* resource misallocation. First, I show that the allocation of capital across entrepreneurs is influenced by their caste. In particular, low-caste (LC) and middle-caste (MC) entrepreneurs have a higher average revenue product of capital, $arpk$, relative to high-caste (HC) entrepreneurs, whereas no such dispersion is visible in the average revenue product of labor, $arpl$. Furthermore, the majority of the cross-caste dispersion in $arpk$ is driven by small and young firms and is concentrated in financially underdeveloped regions in India.

Motivated by these facts, I develop a quantitative model of entrepreneurship to evaluate the relative importance of productivity, technology, and access to credit in explaining the cross-caste dispersion in $arpk$. Through the lens of the model, the majority of differences in $arpk$ are explained by stringent borrowing constraints for non-HC individuals, whereas asymmetries in technology and productivity play a minor role. I find that raising the borrowing capacity of non-HC firms to the level of HC firms would increase aggregate total factor productivity (TFP) by 6%, whereas eliminating such asymmetries in technology and productivity increases it by

[1] See Hall and Jones (1999) and Caselli and Feyrer (2007) for detailed analyses on cross-country productivity differences.

[2] See Munshi (2016). Traditionally, entrepreneurship and financial intermediation belonged to one group called "Vaishyas"; however, these occupations have spilled over to other high castes such as "Brahmins" and "Kshatriyas"; see Damodaran (2008). The high castes represent 35% of the total population.

an additional 4%. Moreover, the model allows me to decompose TFP gains along two margins. First, among active entrepreneurs, a reduction in the misallocation of capital due to differential access to credit across firms of different castes is responsible for 75% of the TFP gains. Second, a reduction in the misallocation of talent in the economy, where productive but poor non-HC entrepreneurs can enter while unproductive but wealthy HC entrepreneurs exit, explains the rest.

I test the model predictions by exploiting the heterogeneity in financial development across various states in India. This approach helps me to evaluate how limited access to credit affects the performance of firms owned by non-HC individuals and its overall welfare implications for the non-HC population. My model explains most of the variation in the cross-caste dispersion in $arpk$ across states. I find that, consistent with the model predictions, moving from the least to the most financially developed state in India, $arpk$ differences between LC and HC entrepreneurs decline from +40% to essentially zero, whereas non-HC households' consumption and asset-holdings increase substantially and converge toward that of HC households.

My empirical analysis exploits data from the Micro, Small and Medium Enterprises (MSME) census of 2006. This dataset provides exhaustive balance sheet information, along with the caste of the enterprise owner and employees, a feature missing in other commonly used firm-level datasets in India.[3] This approach allows me to dissect the data along the caste-dimension and compute various measures of firm performance. Using this dataset, I establish three main stylized facts.

First, within a sector, LC and MC entrepreneurs have 30% and 13% higher $arpk$ relative to HC entrepreneurs, respectively. Moreover, such differences are 6 percentage points higher in rural areas relative to that of urban areas. This evidence is consistent with the fact that, to this day, the caste system is strictly enforced in rural areas, where the majority of the Indian population resides.

Second, I find that most of the cross-caste *dispersion* in $arpk$ is driven by small and young firms. In particular, moving from the smallest to the largest firm in the economy, $arpk$ for LC firms declines from being 30% higher than that of HC firms to essentially nil. A similar convergence is also documented over firm age; however, in this case, substantial $arpk$ differences remain even for older firms in the sample.

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

A high $arpk$ for non-HC entrepreneurs is compatible with other facts in the data: these entrepreneurs are relatively poorer (i.e., their financial wealth is limited), more likely to operate in labor-intensive sectors and use conventional means of production, and less likely to be linked with institutional (bank) financing.

To rationalize these facts, I build a quantitative model of entrepreneurship in which agents

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

from different castes can choose to become either entrepreneurs or workers in the context of *caste-dependent technology, productivity, and access to credit*. Moreover, the model allows for intertemporal savings to capture the self-financing channel. The model serves two main purposes. First, it helps me to disentangle the impact of fundamentals such as technology and productivity from that of potential cross-caste heterogeneity in financial frictions on the $arpk$ dispersion. Second, it helps me to evaluate the welfare implications of such asymmetries at both the extensive and intensive margins.

The quantitative predictions crucially depend on the identification of four sets of parameters, namely, the technology that determines the scale of operation, the dispersion and persistence of the productivity distribution, and the degree of financial frictions. I exploit data from multiple sources to precisely estimate all of these parameters. In particular, first, the moments of the income distribution for each caste are used to pin down span-of-control parameters, which determine the scale of operation of firms. Second, dispersion of the productivity distribution in the model is pinned down by employment distribution for each caste. Third, the degree of financial frictions is estimated by matching credit-to-output ratios. Fourth, the persistence of productivity over time, a crucial parameter that controls the efficacy of the self-financing channel (see Midrigan and Xu 2014), is calibrated with the autocorrelation of output. It is important to note that all of these parameters are jointly estimated in the stochastic steady state.[4]

The model estimates substantial differences in access to credit and dispersion in the ability distribution, whereas estimated values for span-of-control parameters and persistence in ability are quite similar across castes. In particular, the model identifies a smaller span-of-control parameter, a less persistent and less dispersed productivity dispersion, and stricter borrowing constraints for non-HC firms relative to those of HC firms. Furthermore, the model can explain around 80% of the value computed in the data for the cross-caste dispersion in $arpk$. In particular, the $arpk$ of LC and MC entrepreneurs is 21% and 13% higher than that of HC entrepreneurs, respectively, and these differences are primarily, around 70%-80%, driven by limited access to credit for non-HC entrepreneurs. The model identifies financial frictions to be 34% and 23% more stringent for LC and MC entrepreneurs relative to those of HC entrepreneurs, respectively. Such constraints not only lower the borrowing capacity of incumbents but also hinder the entry of non-HC entrepreneurs. As a result, the model estimates a firm ownership rate of 16% and 42% for LC and MC individuals, respectively, and these values are quite close to the ones found in the data (17% for LC and 46% for MC).

The model is able to capture the heterogeneity in the life-cycle dynamics of firms that are owned by different castes. In particular, non-HC entrepreneurs not only enter with a smaller firm size, but also grow slower over time relative to HC entrepreneurs. These differences arise from a combination of two forces: limited borrowing capacity and the small scale of production technology. Therefore, similar to what I find in the data, the size of firms diverges across castes as firms become older. Further, in line with the stylized facts, the model captures a declining trend in the cross-caste dispersion in $arpk$ over firm age and firm size; however, even among the oldest firms, substantial differences remain, owing to the fact that older non-HC firms – that are most likely to be unconstrained – have a high $arpk$ because they use small-scale production

[4] For example, less stringent financial frictions reduce the dispersion in the employment distribution, whereas, the thicker tail of the ability distribution makes it more dispersed. Therefore, a combination of parameters is identified together in the stochastic steady state.

technology.

In the data, I document that more financially developed states also distribute credit more efficiently across castes (i.e., cross-caste differences in the credit-to-output ratio decline). In the same spirit, I solve the model with different levels of financial development to replicate different states in India. The model predicts a steeply declining $arpk$ for LC entrepreneurs over states' credit-to-output ratios. Enhanced borrowing capacity causes LC firms to become more capital intensive as the shadow cost of capital declines. Meanwhile, the efficient allocation of capital increases states' output per capita, which in turn increases household consumption and spurs savings. Such improvement in financial markets primarily benefits marginalized individuals (i.e., non-HC agents in the model).

In what follows, I use the model to conduct various counterfactual exercises. First, I allow non-HC entrepreneurs to have a borrowing capacity that is similar to their HC counterparts. The model identifies gains of 6% in aggregate TFP and 8% in income per capita. Second, an additional 4% of TFP gains are realized once I allow non-HC entrepreneurs to have a technology and ability distribution that is similar to that of HC entrepreneurs. Further, I use the model to decompose TFP gains at the extensive and intensive margins. First, the reallocation of capital from unproductive HC entrepreneurs to more productive non-HC entrepreneurs increases the allocative efficiency of the economy; therefore, as a result, the dispersion in $arpk$ declines by 13%. These changes at the intensive margin explain 75% of the TFP gains. Second, the reduction in borrowing constraints induces the entry of more non-HC entrepreneurs. The share of LC enterprises increases from 16% in the benchmark economy to 29%, whereas the share of MC entrepreneurs decreases from 42% to 35% – that is exactly proportional to their respective population weights. Moreover, because of the excess entry of entrepreneurs, demand for capital and labor increases. This implies a 47% higher interest rate, which further led to the exit of unproductive HC firms and explains the rest of the TFP gains. In the end, I conclude that these TFP gains may represent 15% of the overall gains mentioned in Hsieh and Klenow (2009).[5]

Finally, I provide evidence to rule out alternative explanations that are most likely to predict $arpk$ dispersion across castes but are not directly linked to financial frictions, such as imperfect competition and the heterogeneous output elasticity of capital. I show that markup heterogeneity across castes is unable to account for the $arpk$ dispersion. Further, I compute a quantity-based measure of the average product of capital, apk, and document that it is even higher for non-HC firms than $arpk$. In the end, I also take into account the variation in the output elasticity of capital and show that it does not explain the majority of the cross-caste $arpk$ dispersion.

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.[6] More specifically, a number of papers relate ethnic heterogeneity and misallocation. Hsieh et al. (2019) 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 ethnic heterogeneity

[5] Hsieh and Klenow (2009) argue that if capital and labor were efficiently allocated in India, then TFP would be around 40%-60% higher in the manufacturing sector. However, it is important to note that the model used in this paper is different from the one used in their paper.

[6] Papers on misallocation in India include Hsieh and Klenow (2014), Garcia-Santana and Pijoan-Mas (2014), and Asturias et al. (2019).

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.[7]

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 average products 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 to credit.* They find that a lender of a certain caste increases credit access and reduces collateral requirements for a borrower of the same caste. In general, it is more likely that an owner of a bank, a bank manager or a loan officer is an HC individual.[8] This implies that LC and MC individuals are more likely to face unfavorable loan conditions. This paper formalizes the idea of caste specific borrowing limits or financial constraints in a parsimonious way.

This paper also contribute to the literature that quantifies the impact of financial frictions on aggregate TFP (see, e.g., Banerjee and Moll 2010, Buera et al. 2011, Buera and Shin 2013, Midrigan and Xu 2014, Hopenhayn 2014, Moll 2014 and Buera et al. 2015). In particular, this paper tries to quantify the role of heterogeneity in the degree of financial frictions faced by different types of entrepreneurs.

The remainder of the paper is organized as follows. Section 2 describes the institutional setup, and Section 3 describes the data. The stylized facts are documented in Section 4. Section 5 presents the theoretical framework. Section 6 describes the quantification exercise and discusses the main results and Section 7 provides an analysis of firm-specific factors, other than financial frictions, that may cause $arpk$ dispersion across castes. I summarize the findings in Section 8.

2 Institutional Setup: The Caste System

The caste system is a form of social stratification that divides people into rigid hierarchical groups based on their occupation. For centuries, caste dictated customary social interaction, exclusion and endogamy.[9] In order of hierarchy, these are the Brahmins (priests and teachers), Kshatriyas (rulers and soldiers), Vaishyas (merchants and traders) and the Sudras (laborers and artisans); see figure A.1. Further, there are two additional groups that fall outside the caste system. The first one embodies the group of people traditionally known as Dalits.[10] The second group of people is known as Scheduled Tribes. They have been subject to various forms of discrimination including *barriers to access capital and firm creation*.

[7]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).

[8]In their sample, 74% of the lenders belong to high caste.

[9]Bidner and Eswaran (2015) have describe the caste system as a 3,500 year old system within the context of the four principal castes also known as varnas (Deshpande 2010). Figure A.1 in Appendix A provides the caste structure in detail.

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

For the remainder of the paper, I ignore the micro structure of the caste system and primarily focus on a very broad definition; that is, low-caste individuals are denoted by "LC," which includes the Schedules Castes and Scheduled Tribes; middle-caste individuals are denoted by "MC," which includes the Sudras (also known as Other Backward Castes, OBC, which fall between the traditional upper castes and the lowest), and the high caste is denoted by "HC," which includes the rest.[11] The castes differ in many dimensions; however, I focus on one particular margin: access to credit markets. This paper, using a general equilibrium setting, argues that low-caste individuals face stricter borrowing limits because of imperfect access to credit markets. Tighter borrowing limits could be a result of statistical or taste-based discrimination.[12]

3 Description of the Data

In this paper I use the Economic Census of India (EC) 2005, Micro, Small and Medium Enterprises (MSME) census of 2006-2007, Indian Human Development Survey (IHDS) 2005, Annual Survey of Industries (ASI) 2006 and National Sample Survey (NSS) 2006. Most of the new empirical facts are drawn from the MSME 2006-2007, therefore, I provide its details below, and the details of other datasets are in Appendix A. The main advantage of using the MSME and EC is that they provide the caste of the enterprise owner.[13]

MSME Census: The MSME dataset consists of two parts: a census of registered MSMEs and a survey of unregistered MSMEs.[14] In particular, the dataset 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, bonuses, and so on. The measure of output is gross value added. The amount of loan outstanding captures all the loans from formal and informal sources, where informal sources include local moneylenders, friends and relatives. There are 1.4 million observations left after the cleaning process, which is described in detail in Appendix A. The descriptive statistics are provided in table 1.

MSME Synthetic Panel 2005-2007: The MSME census also provides retrospective information on output for the firms that survive upto 2007. This allows me to construct a balanced

[11] The rest includes Brahmins, Kshatriyas, and Vaishyas (as well as several religions). Traditionally, the caste system has been part of Hinduism, but in modern India we also find its presence in other religions. 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.

[12] This includes a lack of entrepreneurial networks that could provide trade credit or lack of own-caste non-institutional financial intermediaries.

[13] MSME and EC are not commonly used as the ASI or the CMIE Prowess. Researchers do not use the Economic Census more frequently primarily because it does not provide balance sheet information of the enterprise and also lacks a panel dimension. The MSME census does provide balance sheet information; however, it omits large firms and does not have a panel dimension either.

[14] Registration 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 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."

panel of MSMEs for the three-year period, 2005-2007. This synthetic panel allows me to compute statistics such as the auto correlation of firms' output, which is crucial to pinning down the persistence in the ability distribution; (see Appendix A for more details).

Table 1: Summary Statistics- MSME 2006

	HC		MC		LC		Overall
	All	%	All	%	All	%	
Observations (000s)	742	49%	550	40%	145	11%	1437
Employees	2.9	-	2.3	-	1.9	-	2.5
Output (000s)	219	-	104	-	81	-	146
Wage-bill (000s)	79	-	55	-	35	-	61
Capital (000s)	516	-	172	-	115	-	298
Credit (000s)	110	-	42	-	16	-	65
Age	6.7	-	6.1	-	6.7	-	6.5

Notes: Summary statistics for MSME census 2006. Employees is mean employment, capital is mean value of fixed-assets, output is mean value-added and credit is mean amount of outstanding loans. Age is mean years since initial year of production. Percentages indicate percentage of enterprises in a group with respect to all enterprises. Sampling multipliers are applied to compute averages.

4 Stylized Facts

This section illustrates the observed differences in the average product of capital, $arpk$, and average product of labor, $arpl$, across castes. In particular, it shows that $arpk$ is substantially different across castes, whereas such differences in $arpl$ are essentially nil. Further, I document that the majority of such differences are found among small and young firms. Finally, this section showcases a remarkable convergence in cross-caste $arpk$ over regional financial development.

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

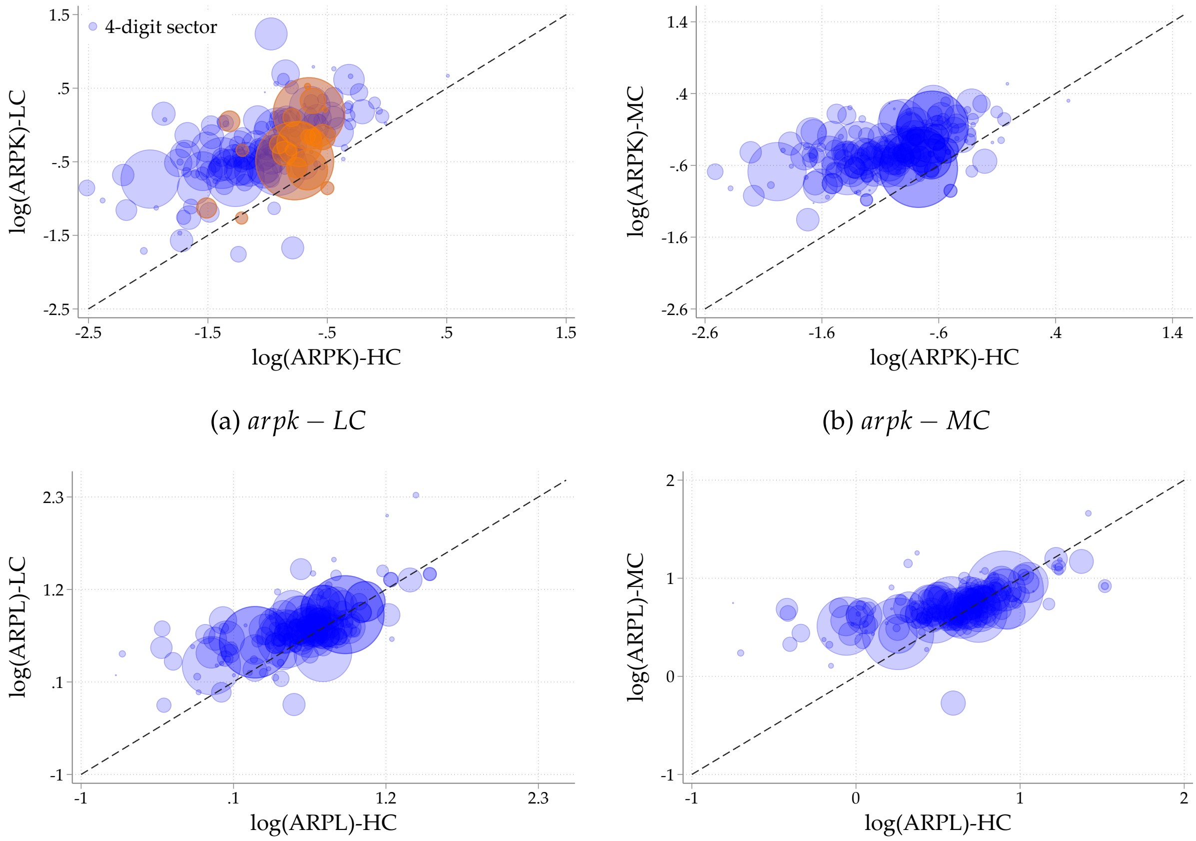
In this section, I divide firms by the caste of their owner. The average product of capital and labor for firm i in sector s with owner of caste c is described as

$$arpk_{isc} := ln(ARPK_{isc}) = ln(Y_{isc}) - ln(K_{isc}),$$

$$arpl_{isc} := ln(ARPL_{isc}) = ln(Y_{isc}) - ln(L_{isc}).$$

The variable Y_{isc} is gross value added, K_{isc} is capital, and L_{isc} is labor input, measured as wage bill. Employment is an imperfect of labor input because it fails to capture actual hours worked and quality; therefore, similar to Hsieh and Klenow (2009), I use the wage bill. I compute the sectoral averages of $arpk$ and $arpl$ for each caste. The sectors are defined according to the National Industry Classification 2004 (NIC 2004), and there are 211 sectors at the 4-digit level. In Figure 1a, I plot the average $arpk$ of LC firms against that of HC firms. It is evident that the differences in $arpk$ exist in most of the sectors, while LC firm have a higher $arpk$ relative to HC firms. Similar results are documented for MC firms (see Figure 1b). Moreover, differences persist in sectors such as food products and beverages; tanning and dressing of leather; and

Figure 1: *arpk* and *arpl*: MSME 2006-2007



(a) $arpk - LC$ (b) $arpk - MC$

(c) $arpl - LC$ (d) $arpl - MC$

Notes: The blue circle represents a 4-digit sector (211 in total). The orange circle represent sectors with high LC participation, such as food products and beverages (NIC-15); tanning and dressing of leather; and manufacture of luggage, handbags, saddlery, harness and footwear, apparels, or furniture (NIC-18,19). Sampling weights are applied.

manufacturing of luggage, handbags, saddlery, harness and footwear, and apparels, where the enterprise ownership of low castes is quite substantial (see Figure 1a). However, when I plot the *arpl* of non-HC firms against that of HC firms, no such differences are documented (see Figure 1c for a comparison of LC and HC firms and Figure 1d for MC and HC firms).[15]

To evaluate within-sector *arpk* differences and to control for regional heterogeneity, I run the following regression;

$$ln\, Y_i = \beta_0 + \beta_1 \mathbb{1}_{L-CASTE} + \beta_2 \mathbb{1}_{M-CASTE} + \Gamma + \epsilon_i. \quad (1)$$

The dependent variables are $\{arpk, arpl\}$. The main explanatory variables are the dummies for the low-caste firms, $\mathbb{1}_{L-CASTE}$, and the middle-caste firms, $\mathbb{1}_{M-CASTE}$, whose corresponding coefficients are β_1 and β_2. The estimators $\widehat{\beta_1}$ and $\widehat{\beta_2}$ are interpreted as the log points difference in the dependent variable between the low- and high-caste firms and the middle- and high-caste firms, respectively. The regressions include sector and state fixed effects. Additionally, there is a vector of controls, Γ, which includes gender and religion fixed effects.

The estimates suggest that MC and LC firms have 14% and 30% higher *arpk* , whereas

[15]For robustness, see Figure A.2 in Appendix A, which provides 5-digit sector classification with 633 sectors.

arpl is 5% lower for MC firms and no such differences for LC firms are observed relative to HC firms, respectively (see Table 2 specifications 1 and 3). In what follows, I explore how cross-caste dispersion in *arpk* differs across rural and urban areas. To do so, I interact the caste dummies with the urban dummy, which allows me to disentangle the average effect of being in urban areas on non-HC firms' *arpk* relative to that of HC firms. In particular, I run the following regression:

$$\begin{aligned} ln\, Y_i = &\gamma_0 + \gamma_1 \mathbb{1}_{L-CASTE} + \gamma_2 \mathbb{1}_{M-CASTE} + \gamma_3 \mathbb{1}_{L-CASTE} \times \mathbb{1}_{Urban} \\ &+ \gamma_4 \mathbb{1}_{M-CASTE} \times \mathbb{1}_{Urban} + \gamma_5 \mathbb{1}_{Urban} + \Gamma + \epsilon_i, \end{aligned} \tag{2}$$

where $\mathbb{1}_{Urban}$ is the dummy variable for urban areas, and γ_3 and γ_4 represent the additional effect on the dependent variable of being in urban areas relative to rural areas for LC and MC firms, respectively. The estimates of γ_3 and γ_4 are negative, suggesting lower *arpk* for non-HC firms (see Table 2).

Table 2: ARPK and ARPL across castes

	(1)	(2)	(3)	(4)
Dep. Var.	*arpk*	*arpk*	*arpl*	*arpl*
MC	0.138	0.160	-0.0537	0.0044
	(0.019)	(0.022)	(0.015)	(0.022)
LC	0.299	0.311	-0.0063	0.0402
	(0.035)	(0.041)	(0.030)	(0.039)
URBAN		-0.0541		0.105
		(0.022)		(0.022)
MC × URBAN		-0.0591		-0.0994
		(0.027)		(0.029)
LC × URBAN		-0.0573		-0.0674
		(0.038)		(0.031)
Obs. (millions)	1.4	1.4	1.4	1.4
R-squared	0.45	0.45	0.45	0.45
State & NIC4 FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓

Notes: Results from the enterprise level regression using equations 1 and 2. Dependent variables are in logs and shown in column headings. The variables *arpk* and *arpl* are the average products of capital and labor, respectively. M-caste is the dummy variable for the middle-caste enterprises. L-caste is the dummy variable for the low-caste enterprises. The vector of controls, Γ, includes region, gender and religion fixed effects. Robust standard errors are in parentheses, clustered at caste, region and sector levels.

The evidence that non-HC firms have a high *arpk* is consistent with many models in which small firms with high returns are constrained from expanding. In these models, marginal products are proportional to average products under the assumption of a Cobb-Douglas production function; therefore, a high *arpk* implies a high shadow cost of capital. It also suggests potential technological differences, in that HC firms are using modern capital-intensive techniques of production. Moreover, as expected, such constraints are more likely to bind in rural areas, where the caste system is more salient, relative to urban areas; therefore, high *arpk* for non-HC firms in rural areas is consistent with this view. The next two facts will provide more corroborative evidence and strengthen this view.

Finally, given the fact that *arpl* is not different across castes, from here onward, I will primarily focus on the observed dispersion in *arpk* and explore its various facets.

Fact 2: ***arpk*** **differences across castes decline with size and age.**

Here I document the evolution of *arpk* differences over firm size and firm age. I divide enterprises into five different size bins, defined by employment and compute β_1 for each size bin using the regression model described in equation 1. As shown in Figure 2a, differences persist among smaller enterprises, but they are essentially nil for large firms. In fact, if one looks at enterprises with more than 100 employees, the LC entrepreneurs have a lower *arpk* relative to HC entrepreneurs. This evidence suggests that the technology differences across castes or the presence of capital adjustment costs cannot explain all the dispersion in *arpk*.[16]

Furthermore, *arpk* differences are heterogeneous across firms of different age groups. First, I find that the mean age is similar for LC and HC firms, whereas MC firms are half a year younger than other firms (the median age is 5 years for all castes; see Figure A.3 in Appendix A for the age distribution). Further, I pair enterprises into five different age groups and compute β_1 using the regression model described in equation 1 for each group. Figure 2b shows that *arpk* is highest for young LC entrepreneurs, +35% relative to that of HC firms, and it declines over age. This result is consistent with the existing evidence on financial frictions and the firm life-cycle (e.g., see Hadlock and Pierce 2010) that suggests that size and age are good predictors of financial constraints such that young and small entrepreneurs are most constrained, and large and old firms are least likely to be constrained.[17] However, even among the oldest firms in the data, the *arpk* for LC firms is substantially higher than that of HC firms (+25%), pointing toward potential technological differences.

Fact 3: ***arpk*** **differences across castes decline over regional financial development.**

In this section, I further explore the effect of financial development on the cross-caste dispersion in *arpk*. Ayyagari et al. (2014) document large and persistent differences in financial development across states in India. Meanwhile, Munshi (2016) documents low mobility in India. Therefore, concerns regarding endogenous spatial sorting of entrepreneurs are quite low.

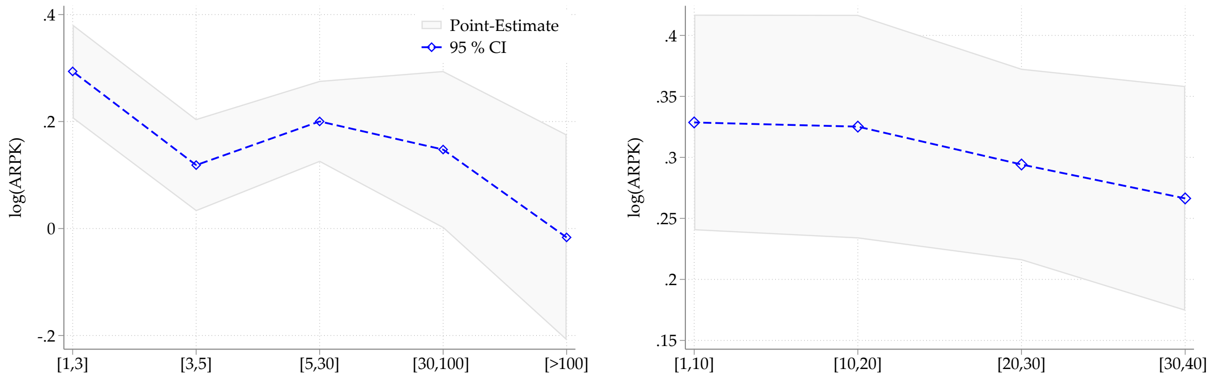
In what follows I construct a credit-to-output ratio for each state and use it as a measure of financial development.[18] The observed differences in *arpk* across castes fall as the credit-to-output ratio increases (see Figure 3). In particular, LC firms have an *arpk* that is 40% higher than that of HC firms in states with the lowest financial development such as Bihar, Jharkhand, and Uttar Pradesh, but no such differences are observed in states such as Maharashtra (see

[16]The presence of non-convexity in the production technology in capital usage could also lead to differences in *arpk* across large and small firms. The presence of non-convex capital adjustment costs, including time-to-build, create dispersion in *arpk* among small and large firms. However, such forces can not explain differences within a size group.

[17]I use a cross section to provide evidence on *arpk* over firm age. It is plausible that the LC enterprises that are born in different years are inherently different from each other. The data do not allow me to rule out such a hypothesis.

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

Figure 2: LCs' ARPK over Size and Age



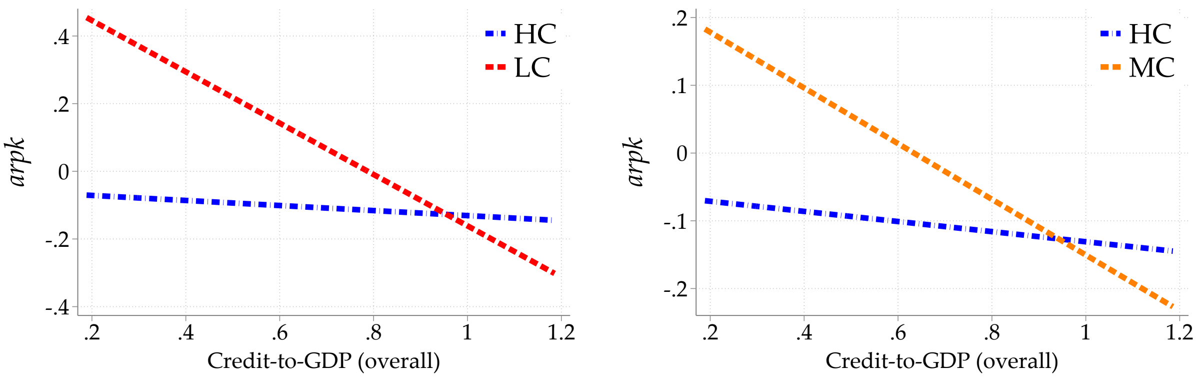
(a) Employment

(b) AGE

Notes: The blue line represents value of the L-caste dummy in regression specification 1. White bands represent 95% confidence intervals.

Figure 3a). More interestingly, *arpk* in absolute terms declines for LC entrepreneurs but is relatively stable for HC entrepreneurs. Similar trends are documented for MC firms as well (see Figure 3b). This evidence is consistent with the models of financial frictions in which better functioning financial markets improve credit allocation and selection among entrepreneurs in the economy.[19]

Figure 3: ARPK and External Financing



(a) Low-Caste Firms

(b) Middle-Caste Firms

Note. All lines represent linear regressions including sector fixed effects and control variable Γ. LC = low caste, MC = middle castes, and HC = high Castes. Sampling weights are applied. Regression details are provided in Table A.1 in Appendix A.

In this section, I have documented three stylized facts that suggest misallocation of capital across castes. Historically, LC and MC individuals had limited access to entrepreneurship and capital markets. Even today, they are relatively poorer (i.e., their financial wealth is limited), more likely to operate in labor-intensive sectors and use conventional means of production, and less likely to be linked with lending organizations (see Table 1). Furthermore, such constraints are most likely to affect small and young non-HC firms and Fact 2 is in line with this notion. I further provided suggestive evidence on the role played by underdeveloped finan-

[19]In these models, credit is allocated based on financial wealth or cash flows and not on productivity. Therefore, wealthy but unproductive individuals create firms and are also leveraged.

cial markets in explaining such dispersion by exploiting the heterogeneity in regional financial development. However, the welfare implications of this dispersion are not straight forward and could be a result of differences in fundamentals such as the productivity process and technology, as well as heterogeneity in access to credit. To shed light on different sources of the $arpk$ dispersion, in the next section, I build a general equilibrium model in which agents of different castes make occupation choices in the context of caste-specific borrowing limits, technology and productivity. Through the lens of the model, I link the dispersion in $arpk$ partly to the misallocation of capital and quantify the role played by fundamentals and access to credit in explaining such dispersion. Finally, I evaluate the welfare implications of cross-caste dispersion in $arpk$ in the model.

5 Theoretical Framework

The model is an extension of the framework used in Buera et al. (2011) and Buera and Shin (2013). Time is discrete and there is a measure M of infinitely lived agents that are heterogeneous across productivity z, assets a, and caste c. Every period, agents choose to become either workers or entrepreneurs based on their wealth a and entrepreneurial productivity z, and this occupational choice is represented by o_t. Financial wealth is determined endogenously by the consumption-saving problem described below, whereas productivity follows a stochastic process such that agents retain their last-period productivity z_t with probability ψ_c, and with probability $1 - \psi_c$, they draw their new productivity from a Pareto distribution with scale parameter η_c. The parameter ψ_c represents the persistence, whereas η_c captures the dispersion in the productivity process. If $\psi_c = 1$, 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 $\psi_c = 0$, 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:

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

The entrepreneurs have access to a decreasing returns to scale production function $f(z, k, l) = z\,(k^{\alpha} l^{\beta})^{1-\nu_c}$ where $\alpha + \beta = 1$ and $1 - \nu$ is the span-of-control parameter that varies between 0 and 1. The output price is normalized to one. An entrepreneur rents capital k in the financial market (more discussion follows below) and hires labor l to produce y units of a single good. Also, entrepreneurs need to pay a per-period fixed cost of operation κ.

Financial Markets: There is a perfectly competitive intermediary that receives deposits from savers and lends these funds to entrepreneurs. There is no intermediation cost; that is, 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.[20] Specifically, the capital constraints take the following forms:

$$k_t \leqslant \lambda_c\, a_t; \quad a_t \geqslant 0,$$

where λ_c measures the degree of credit constraints and varies from 1 to ∞.[21] Individuals of certain caste c with $\lambda_c = 1$ will operate in a zero-credit environment (financial autarky), whereas $\lambda_c = \infty$ will allow individuals to borrow according to their productivity and not based on their financial wealth.[22]

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

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

The workers' value function is given by

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

The entrepreneurs' value function is given by

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

5.1 Recursive Competitive Equilibrium

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

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

[20] 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. For example, more than 84% of the loans required collateral in India in 2014 according to the World Enterprise Survey 2014, World Bank.The micro-data for the WES are available: `http://microdata.worldbank.org/index.php/catalog/2225/get_microdata`.

[21] This type of financial frictions can be micro-founded with the following limited enforcement problem. Entrepreneurs deposit their financial wealth a and can borrow capital k from financial intermediaries at the beginning of the period, whereas, financial institutions can recover upto $\frac{1}{\lambda_c}$ times the rented capital in case of default. The entrepreneur will lose financial wealth a but is included in the future economic activity. In this scenario, financial intermediaries will lend upto $\lambda_c a$, which makes default incentive incompatible.

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

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

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

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

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

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

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

6 Quantitative Analysis

In this section, I evaluate the role of technology, productivity, and access to credit in explaining the cross-caste dispersion in the *arpk*. Further, I quantify the TFP losses due to resource misallocation generated by such asymmetries at the extensive and intensive margins. I begin by calibrating the model to the manufacturing sector of India using data from multiple sources.[23] I then conduct various experiments to validate the model. In particular, I vary the parameters that change the credit-to-output ratio across castes to mimic various regions in India and to draw verifiable predictions from the model. Finally, I evaluate the losses from financial and fundamental asymmetries (includes technology and productivity asymmetries) in aggregate TFP.

6.1 Calibration

The calibration strategy is based on Buera and Shin (2013) and Midrigan and Xu (2014). Overall, I need to specify values for 17 parameters: span-of-control of production technologies, dispersion and persistence in ability distributions, degree of financial frictions, fixed cost of operation, discount factor, coefficient of risk aversion, capital depreciation rate, and physical capital share. The parameterization proceeds in two steps. First, I fix a set of parameters that are fixed outside the model (e.g., the depreciation rate). The fixed parameters are difficult to identify with the available data, so I use the values that are commonly used in the literature. Second, given the values of these fixed parameters I choose the remaining parameters to match the salient features of the economy (e.g., the distribution of employment and business income, among others).

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

6.1.1 Data for Empirical Moments

As discussed in Section 3, the MSME dataset, which contains variables such as capital stock, the wage bill, output, and credit, only represents firms below a certain threshold level of capital, while the Economic census 2005 contains a universe of firms but only provides information on the caste of the owner and the number of employees. Therefore, I use the Economic Census 2005 to compute the employment distribution for the overall economy and for each caste.[24] Meanwhile, the serial correlation of output and the credit-to-output ratio for each caste are evaluated using the MSME dataset. For this reason, I need to define MSME firms in the model, such that I can compute the model counterparts of the empirical moments.

To define MSME firms in the model, I need to compute the MSME capital threshold stock $\bar{K}$ in the model. I evaluate $\bar{K}$ such that the total output produced by firms with capital stock below $\bar{K}$ is matched to its data counterpart. The share of output produced by MSMEs in the data in 2006 is computed using the ASI-NSS 2006 dataset. According to the reports generated by the Ministry of Micro, Small and Medium Enterprises in India, the threshold to be defined as MSME is in "cumulative investment in plant and machinery (original cost)" (see Garcia-Santana and Pijoan-Mas 2014 for more details).[25] This variable is available in the ASI-NSS dataset as *value of plant and machinery owned by the firm*. I use the MSME threshold to compute the share of output produced by firms that are below this threshold, and it stands at 41%.[26]

The income distributions and population shares for each caste are computed using IHDS 2005 data.[27]

6.1.2 Identification

Fixed Parameters: A model period is one year. The structural parameters α, γ, and δ are the same across castes. The annual depreciation rate for capital is $\delta = 0.06$, the capital income share is $\alpha = 0.33$, and the coefficient of risk aversion is $\gamma = 1.5$, following Hsieh and Klenow (2009) and Cagetti and De Nardi (2006).[28]

Fitted Parameters: Given the parameters α, γ, and δ, the model is solved to match certain moments in the data. The discount factor is set at $\rho = 0.844$, the same for every caste, to match the annual interest rate of 5.682% in 2007.[29] The fixed cost of operation is set at $\kappa = 0.10$ to match the relative size of entrants with respect to the incumbents.[30]

The span-of-control parameters $\{1 - \nu_{lc}, 1 - \nu_{mc}, 1 - \nu_{hc}\}$ are set such that the business income share of the bottom 95% of entrepreneurs is the same in the data and the model for each

[24] I use EC 2005 because it is not available for 2006. I compute the employment distribution for ASI-NSS 2006 and Economic census 2013-2014, and it is quite stable over time (see Appendix A).

[25] The limit is 100 million in Indian rupees.

[26] Because of data restrictions, I assumed that the share of MSMEs output as the fraction of total output in 2007 is the same as in 2006.

[27] The business income distribution is computed for the year 2005 in the IHDS because of the absence of data for the year 2007. However, data are available for the year 2012 and the income distribution is very stable over time (see Table A.6 in Appendix A).

[28] The capital income share α is assumed to be the same across castes because of non-availability of data that could be used to measure it credibly (see Section 7 for more detail).

[29] The annual real interest rate in India varies from 2% to 8.34% between 1999 and 2010.

[30] I measure the relative entrant size in the ASI-NSS 2006 dataset that encompasses the manufacturing sector (see Appendix A for more details). I do not allow for heterogeneity in κ, which matters for the misallocation at the extensive margin, across castes in order to focus on financial friction as the sole driver of misallocation. Moreover, as shown in Table 5, the model closely matches the percentage of firms owned by each caste without requiring any heterogeneity in κ.

Table 3: Parameters Value

Parameter	Value	Description
Fixed:		
δ	0.060	Annual depreciation rate physical capital
α	0.330	Physical capital share
γ	1.500	Coefficient of risk aversion
Fitted:		
ρ	0.844	Discount factor
$1-\nu_h$	0.761	Span of control for HC
$1-\nu_m$	0.745	Span of control for MC
$1-\nu_l$	0.745	Span of control for LC
ψ_h	0.927	Persistence in productivity for HC
ψ_m	0.922	Persistence in productivity for MC
ψ_l	0.918	Persistence in productivity for LC
λ_h	1.760	Degree of financial frictions for HC
λ_m	1.370	Degree of financial frictions for MC
λ_l	1.160	Degree of financial frictions for LC
η_h	4.520	Scale parameter of ability distribution for HC
η_m	4.700	Scale parameter of ability distribution for MC
η_l	4.890	Scale parameter of ability distribution for LC
κ	0.100	Fixed cost of operation

Table 4: Model Moments

Targeted Moments	Model	Data
HC:		
One-year autocorrelation of output	0.94	0.94
Employment share of bottom 95%	0.62	0.56
Income share of bottom 95%	0.64	0.67
Population share	0.35	0.35
MC:		
One-year autocorrelation of output	0.96	0.96
Employment share of bottom 95%	0.66	0.72
Income share of bottom 95%	0.67	0.71
Population share	0.36	0.36
Credit/output rel. HC	0.56	0.56
LC:		
One-year autocorrelation of output	0.96	0.94
Employment share of bottom 95%	0.72	0.78
Income share of bottom 95%	0.72	0.72
Population share	0.29	0.29
Credit/output rel. HC	0.27	0.27
Overall Economy:		
Annual interest rate	5.7%	5.7%
Entrants' relative size	0.32	0.23
Credit/output	0.45	0.45
Share of MSME sector	0.41	0.41
Additional moments:		
Overall employment share of bottom 95%	0.64	0.64
Overall employment share of bottom 90%	0.52	0.52
Overall income share of bottom 95%	0.67	0.68
Overall income share of bottom 90%	0.54	0.55

Notes: Employment distribution in the data is evaluated with Economic Census 2005 and income distribution is evaluated with IHDS 2005. The overall credit-to-output ratio is taken from statistics published by the Reserve Bank of India. The credit-to-output ratio for LC and MC relative to HC is computed using the MSME data. One-year autocorrelation of output is computed using the synthetic panel in the MSME data while controlling for sectoral and regional heterogeneity.

caste. A lower $1-\nu_c$ implies a larger scale of operation and higher profits for entrepreneurs, which further makes the income distribution of entrepreneurs more dispersed; therefore, it is informative regarding the production technology used by each caste. Meanwhile, the scale parameters of the ability distribution $\{\eta_l, \eta_m, \eta_h\}$ are set such that the employment share of the bottom 95% of enterprises is matched in the data and the model for each caste. A higher value of a η_c means a thicker tail of the productivity distribution, which further implies a greater employment generation by large firms. This helps the model to distinguish η_c for each caste.

To discipline the persistence of the productivity process $\{\psi_{lc}, \psi_{mc}, \psi_{hc}\}$, I match the one-year autocorrelation of output in the data with its counterpart in the model. A persistent productivity process increases the serial correlation of output and reduces the impact of financial frictions on capital misallocation in the stochastic steady state (see Midrigan and Xu 2014 and Moll 2014). Therefore, heterogeneity in ψ_c allows me to disentangle the effects of borrowing constraints from that of the productivity process.

The parameters related to financial frictions $\{\lambda_{lc}, \lambda_{mc}, \lambda_{hc}\}$ are fixed such that the overall credit-to-output ratio in the economy is the same in the model and the data. Furthermore, the credit-to-output ratios for LC and MC relative to HC are also matched.[31] A higher λ_c implies a larger supply of credit in the economy and hence higher leverage in the economy.

The parameters are estimated using the following routine. For arbitrary values of the vector of parameters, $\Xi = (1-\nu_{lc}, 1-\nu_{mc}, 1-\nu_{hc}, \eta_{lc}, \eta_{mc}, \eta_{hc}, \psi_{lc}, \psi_{mc}, \psi_{hc}, \lambda_{lc}, \lambda_{mc}, \lambda_{hc}, \kappa, \rho)$, I solve the recursive competitive equilibrium and evaluate the stationary distribution in $\{a, z, c\}$. Using this distribution, I compute the business income distributions, employment distributions, and the $\bar{K}$, the capital threshold for MSMEs, such that the share of output produced by them is matched to its data counterpart. I evaluate respective credit-to-output ratios. Furthermore, I draw from the stationary distribution to simulate the economy for three periods, construct a balanced panel of MSME firms, and compute the serial correlation of output in the same spirit of the empirical counterpart. I denote all these simulated moments by $\Omega(\Xi)$ and estimate the fitted parameters $\hat{\Xi}$ using a minimum distance criterion given by

$$\mathcal{L}(\Xi) = \min_{\Xi}(\hat{\Omega} - \Omega(\Xi))' \mathbf{W} (\hat{\Omega} - \Omega(\Xi)). \tag{6}$$

I set the weighting matrix $\mathbf{W} = \mathbf{I}$ and use grid search to find the minimum.

6.2 Results

The fitted parameters from the simulated method of moments are listed in Table 3, and the implied moments of the model, in comparison to their data counterparts, are presented in Table 4. The model closely matches the set of targeted moments as well as a set of additional moments that captures the overall income and size distribution of firms. The model identifies different parameters of technology, productivity, and financial constraints for each caste, and its implications are discussed below.

The scale parameter of the ability distribution is lower for HC individuals compared to that of MC and LC individuals. This stems from the fact that the employment distribution of HC is skewed toward the right, which is achieved in the model by having a thick right tail of the productivity distribution. This further implies that the mean ability is higher for HC

[31] In the MSME dataset, the credit-output ratios for the high, middle and low castes are 0.30, 0.17, and 0.09, respectively.

individuals relative to that of MC and LC individuals. These differences could be interpreted as differences in human capital (proxied by years of schooling) or cognitive abilities, which stems from centuries of discrimination against low castes. Further examination of these differences is beyond the scope of this paper and is left for future research.[32] The persistence of the productivity process is also identified to be lower for LC and MC individuals relative to that of HC individuals. This is the result of their higher serial correlation of output in the data (see Table 4). A lower persistence would also imply higher income uncertainty as there is more occupational switching among non-HC individuals.[33]

The model identifies that MC and LC entrepreneurs operate their firms with a production technology with smaller span-of-control parameter relative to HC entrepreneurs. This is because the business income distribution is relatively more skewed towards right in the case of HC compared to other castes. This implies a small size for LC and MC firms, but with high profitability, a prediction that is verified in the data as well (see Appendix A). Finally, the model implies limited access to credit for LC and MC relative to HC individuals. In particular, the model identifies λ_{lc} to be 34% smaller and λ_{mc} to be 23% smaller than λ_{hc}. This is driven by lower credit-to-output ratio of LC and MC firms relative to that of HC firms.

6.2.1 Misallocation across Castes

The main objective of this paper is to quantify the misallocation of resources across castes and its impact on aggregate TFP. The literature has stressed the role of financial frictions on two different margins of misallocation: the extensive margin and the intensive margin.

The intensive margin refers to the overall dispersion in $arpk$; however, this paper is primarily concerned with the $arpk$ dispersion across castes.[34] The model predicts that LC and MC agents have 13% and 21% higher $arpk$ than that of HC agents. This captures around 70%-80% of the values observed in the data (see Table 5). The dispersion in $arpk$ is driven by two factors in my model. First, difference in access to credit make LC and MC relatively more constrained in the stochastic steady state, thereby increasing the shadow cost of capital.[35] Further, I evaluate the role of asymmetric access to credit in explaining the cross-caste dispersion in $arpk$. To do so, I equalize the parameters governing the degree of financial frictions across castes, keeping all else constant. I find that this leads to a reduction of around 70%-80% of the differences in $arpk$ across HC and non-HC firms.

Second, differences in fundamentals such as technology and the productivity process, exacerbate the dispersion in $arpk$ and explain the remaining 20%-30% of differences in $arpk$ across

[32] 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 villages.

[33] Higher uncertainty about future productivity could stem from various sources – for example, an absence of entrepreneurial networks that could help sustain bad shocks, institutional discrimination, among others. Asker et al. (2014) discuss the impact of higher volatility in productivity on $arpk$ and its potential causes.

[34] The literature refers to the dispersion in the marginal revenue product of capital (MRPK) as a misallocation of capital (Hsieh and Klenow 2009). However, my model implies that the MRPK is directly proportional to the ARPK, $MRPK = \alpha(1-\nu)ARPK$.

[35] The consumption Euler equation for constrained entrepreneurs contains Θ_{t+1}, the shadow cost of capital:

$$\zeta_t^{-\gamma} = \rho \int_{z'} \{\zeta_{t+1}^{-\gamma}(1 + r_{t+1} + \lambda_c \Theta_{t+1})\} d\Pi(z'|z),$$

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

Table 5: Results

	Model	Data
Intensive-margin		
$arpk - MC$	$+13\%$	$+22\%$
$arpk - LC$	$+21\%$	$+34\%$
$k/l - MC$	-11%	-31%
$k/l - LC$	-28%	-58%
Extensive-margin		
$\%\ of\ firms$-LC	16%	17%
$\%\ of\ firms$-MC	42%	46%

Notes: The measures of $arpk$ and capital-intensity(k/l) are computed for MSMEs in both the data and the model and represent their respective values with respect to HC firms in the manufacturing sector. The percentage of firms owned by each caste in the data is computed using the Economic Census 2005. Sampling weights are applied.

castes. Multiple forces are at work here; (i) heterogeneity in the persistence of the productivity process exacerbates $arpk$ differences across castes in conjunction with financial constraints, as lower persistence dampens the channel of self-financing. For non-HC entrepreneurs, past productivity is not a good predictor of future productivity; therefore, it enhances the volatility of business income and induces more occupation switching. (ii) A lower span-of-control implies a higher $arpk$ for LC and MC firms independent of the degree of financial constraints; however, such dispersion in $arpk$ does not directly imply misallocation.[36]

The extensive margin refers to the distorted occupation choice in the context of the model. In particular, in this economy, the productivity threshold of entry $\bar{z}(a, \lambda_c)$ is decreasing in a and increasing in λ_c.[37] Under such circumstances, non-HC individuals' productivity threshold $\bar{z}(a, \lambda_c)$ is higher than that of HC individuals, which implies higher labor-force participation and a lower entrepreneurial rate for the former group. The model does a good job in matching the number of firms owned by each group (see Table 5). For more detailed results on enterprise ownership across castes in the Economic Census 2005, see Table A.2 in Appendix A. Another important implication is that the average productivity of the low-caste entrepreneurs should be relatively higher than that of HC entrepreneurs because only the very productive non-HC agents can operate profitably. A model-consistent measure of firm productivity is given by

$$tfpr := ln(TFPR_{ic}) = ln(Y_{ic}) - \alpha(1-\nu_c)ln(K_{ic}) - \beta(1-\nu_c)ln(L_{ic}),$$

where i represents the firm, c stands for caste and $tfpr$ is revenue productivity.[38] Capital is

[36] However, in models of technology adoption under financial constraints, this could be a potential source of misallocation (see Section 6.4 for detailed discussion).

[37] The max operator in equation 3 pins down the occupation choice $o(a, z, c)$ for each agent such that, whenever the value of being an entrepreneur is greater (lower) than that of being a worker, agents decide to be an entrepreneur (worker). For a certain asset base a, there exists a productivity threshold $\bar{z}(a, \lambda_c)$ such that $\pi(a, \bar{z}(a, \lambda_c), \lambda_c; r, w) = w$. A wealthy but unproductive agent is more likely to enter into entrepreneurship than a poor but productive one. This creates misallocation of talent or misallocation at the extensive margin. An agent with zero wealth can never be an entrepreneur, $\bar{z}(0) \to \infty$, whereas an agent with infinite wealth can be an entrepreneur only if he or she is productive enough, $\bar{z}(\infty) = \underline{z}$.

[38] This measure includes firm-level prices and therefore encapsulates the dispersion in markups as well. However, I do provide more evidence on quantity-based measures and markups (see Section 7).

demoted by K_{ic} and L_{ic} is the wage bill, which is consistent with Section 4. In the data, I find HC entrepreneurs to be less productive than LC entrepreneurs (see Table A.3 in Appendix A), and this effect is captured well by the model, where LC firms are 5% more productive than HC firms. However, the model does not imply any significant difference in the productivity between HC and MC entrepreneurs.

Furthermore, 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 HC firms that are marginally unproductive. As a result, the overall TFP of the economy goes down. I will postpone the discussion on welfare implications until Section 6.4.

6.2.2 Firm Entry and Life Cycle Dynamics

In this section, I discuss the life cycle of firms and shed light on its differences across castes. Similar to Fact 3 documented above, I found that the model predicts declining differences in $arpk$ over the firm life cycle. In particular, Figure 4a shows that the $arpk$ of HC and LC firms declines over employment; however, the decline is faster for LC firms such that no difference in $arpk$ emerges for larger firms in the size distribution. Meanwhile, Figure 4b depicts a similar decline; however, differences do not completely disappear even for older firms in the sample. This model prediction is consistent with what I documented above as Fact 3 in Section 4. These results are driven by the technology differences across castes. LC firms use small scale technology, which implies a higher $arpk$ than HC firms, irrespective of financial frictions.

Finally, Figure 4c shows how firm output grows over its age. Firms enter small because of their limited borrowing capacity; however, with time they accumulate financial wealth and grow in size. It is clear that LC firms enter small and then grow slower relative to HC firms. This is driven by a combination of two forces: limited borrowing capacity and the use of small-scale technology by LC firms. As a result, firm size diverge over age. A similar pattern of life-cycle dynamics emerges in the data as well (see Figure A.4 in Appendix A).

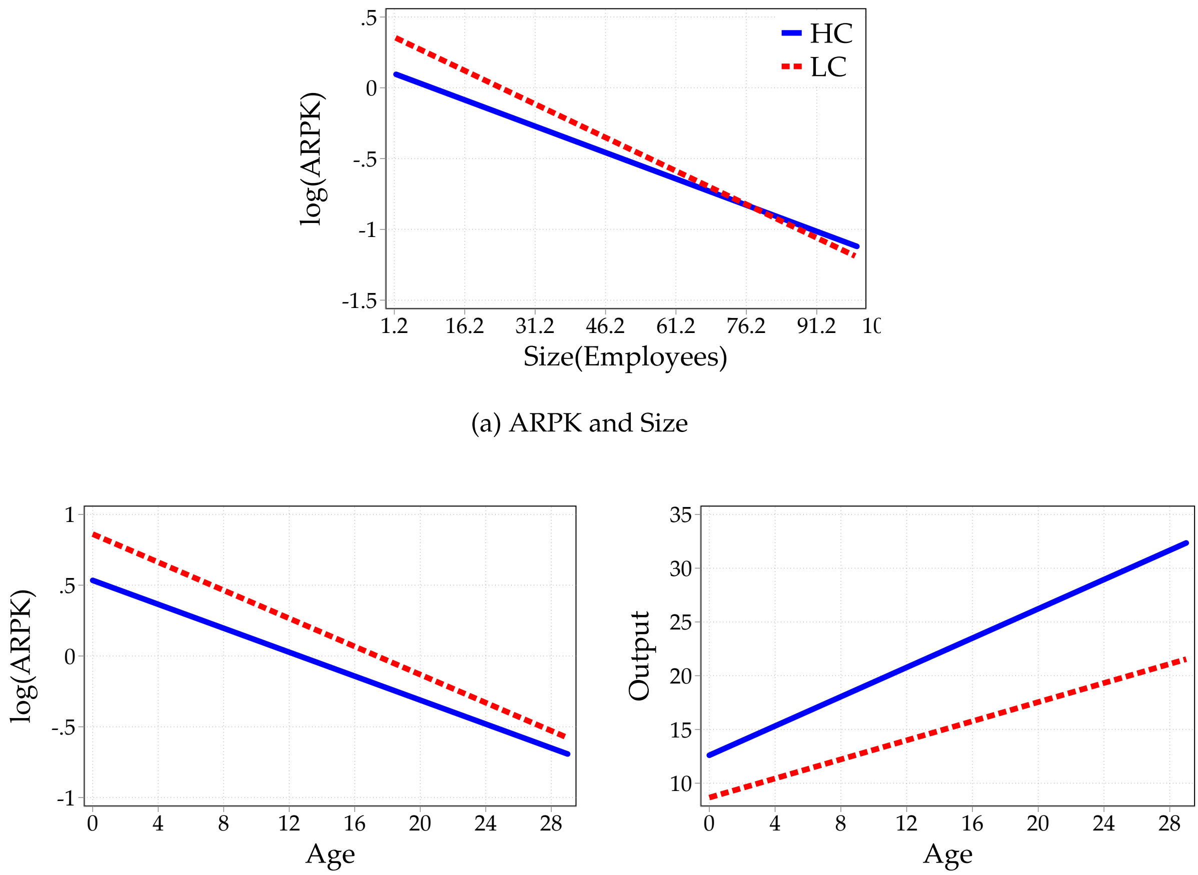
Until now, I have shown that the cross-caste dispersion in $arpk$ is driven by differences in fundamentals and access to credit. In particular, the model estimates stringent borrowing limits for non-HC entrepreneurs and large span-of-control parameter for HC entrepreneurs. The untargeted moments such as $arpk$ and firm ownership for non-HC castes are very well matched to their data counterparts. In what follows, I use the model to evaluate how the dispersion in $arpk$ evolves over regional financial development.

6.3 Regional Financial Development and the $arpk$ Dispersion

In this section, I will revisit Fact 2 in Section 4 in the spirit of the model. First, I document that the states that are more financially developed (i.e., those with a high credit-to-output ratio) distribute credit more efficiently across castes as well. In particular, Figure 5a depicts a positive correlation between the regional credit-to-output ratio and the credit-to-output ratio of LC firms relative to HC firms.[39] Second, I exploit this heterogeneity to further validate the findings of the model by solving the model for different levels of financial development and predicting the dispersion in $arpk$ across castes. In particular, I move the parameter that governs the degree

[39]See Figure A.5 in Appendix A for MC firms.

Figure 4: ARPK and Firm Life Cycle: Model



(a) ARPK and Size

(b) ARPK and Age

(c) Output and Age

Note. All lines represent a linear-fit of the data produced with a benchmark calibration in the model.

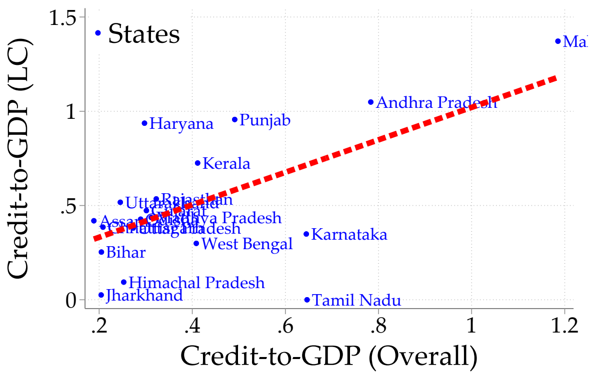
of financial frictions in the model λ_{lc} such that the credit-to-output ratio for LC entrepreneurs relative to that of HC entrepreneurs increases and, thus, the overall overall credit-to-output ratio increases as well (see Figure 6a).[40]

The model predicts a steeply declining *arpk* for LC entrepreneurs, whereas a mild increase is captured for HC entrepreneurs, owing to the enhanced borrowing capacity of and a high interest rate in response to a high demand for capital. As a result, *arpk* differences across castes decline from over +30% in the least financially developed regions to essentially nil in the most advanced ones (see Figure 6b). As a result, increasing borrowing capacity leads LC firms to become more capital intensive (see Figure 6c). I find support for these predictions in the data (see Figure 5b for *arpk* and Figure 5c for capital intensity).

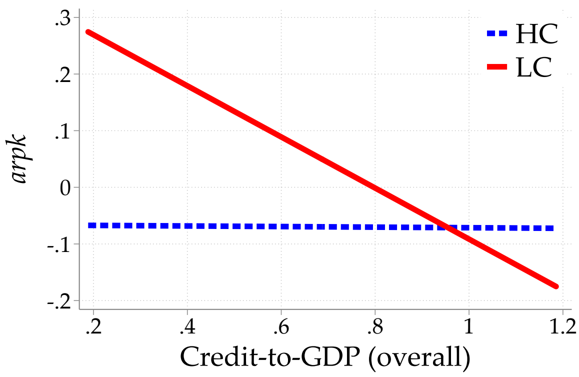
Furthermore, a high borrowing capacity allows the entry of more LC firms relative to the benchmark economy, which further implies a reduction in firm level $tfpr$ of the marginal entrant of LC individuals and a steep convergence toward the average level of $tfpr$ of HC individuals (see Figure A.6 in Appendix A). This prediction is consistent with the evidence that

[40] The model is solved for several values of λ_{lc} between 1 and 2. The regional analysis captures the spirit of Buera et al. (2011), where the improved efficiency of financial sector increases overall welfare. Output per capita, capital intentsity and TFP increase over the regional credit-to-output ratio (see Figure A.8 in Appendix A).

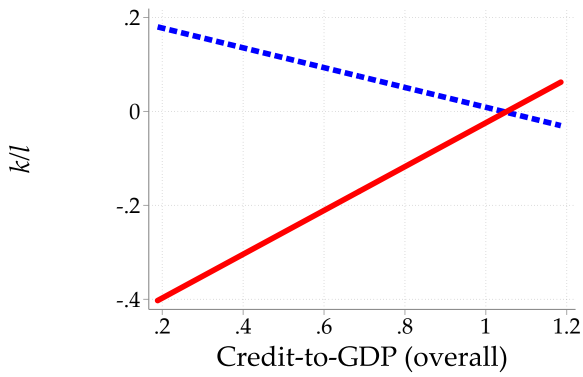
Figure 5: Financial Development and LC Firms-Data



(a) Access-to-Credit



(b) ARPK



(c) Capital-Intensity

Notes: The overall credit-to-GDP ratio is computed with statistics published by the Reserve Bank of India. The credit-to-GDP ratio for LC and MC firms is computed in MSME data. Graphs (b) and (c) present a linear fit of residualized $arpk$ and k/l. Sampling weights are applied

I find in the data; that is, productivity is 40% higher than that of HC firms in less financially developed states to below zero in states with well-functioning financial markets (see Figure A.7 in Appendix A).

I further use a regression model to pin down the elasticity of $\{arpk, k/l, tfpr\}$ to financial development for LC entrepreneurs. In what follows, I interact the caste dummies with the financial development of states Fd_s. The regression specification is

$$ln\, Y_i = \hat{\gamma}_0 + \hat{\gamma}_1 \mathbb{1}_{L-CASTE} + \hat{\gamma}_2 \mathbb{1}_{L-CASTE} \times Fd_s + \hat{\gamma}_3 Fd_s + \Gamma + \epsilon_i, \tag{7}$$

where $\hat{\gamma}_2$ represents the elasticity of the dependent variable to Fd_S with respect to HC entrepreneurs, respectively. The value of $\hat{\gamma}_2$ is significantly negative for $arpk$ and $tfpr$ and positive for k/l, suggesting an improved allocation of credit across castes (see Table 6).

The excess entry of LC entrepreneurs increases demand for capital and labor, which further implies high factor prices such as the interest rate and wages. Moreover, a high interest rate spurs saving and credit growth simultaneously, which increases the asset holdings of

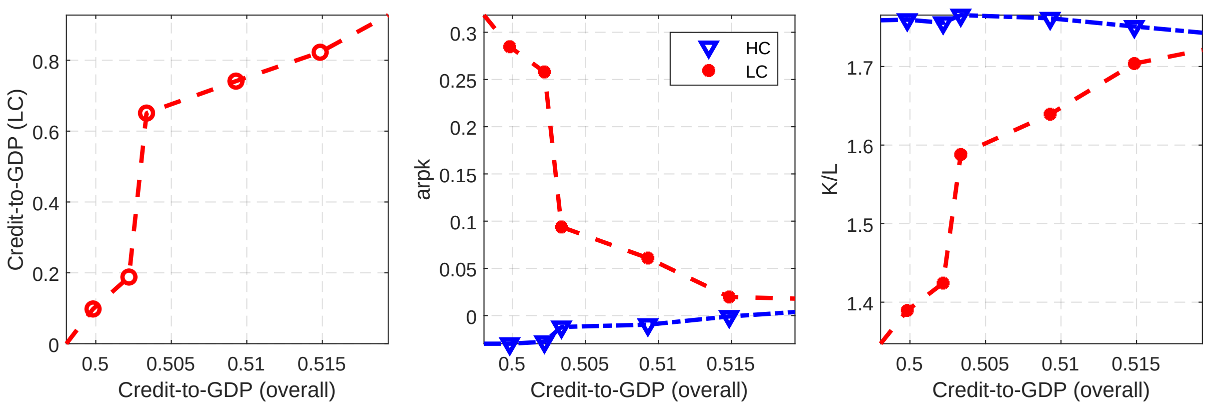
Table 6: Financial Development and LC Firms: Data

Dep. Var.	(1) $arpk$	(2) k/l	(3) $tfpr$
LC	0.538	-0.875	0.416
	(0.101)	(0.109)	(0.175)
Fd	-0.0254	-0.196	-0.254
	(0.085)	(0.104)	(0.073)
LC × Fd	-0.533	0.765	-0.454
	(0.175)	(0.187)	(0.228)
LC-population	1.072	-1.763	0.382
	(0.228)	(0.246)	(0.187)
Observations	624,987	624,987	605,255
R-squared	0.139	0.250	0.075
NIC4 FE	✓	✓	✓
Controls	✓	✓	✓

Notes: Results from the enterprise level regression using equation 7. Dependent variables are in logs and shown in column headings. Fd is an index of financial development across states. The vector of controls, Γ, includes region, gender and religion fixed effects. Robust standard errors are in parentheses, clustered at the caste, region and sector level. Sampling weights are applied.

households (see Figure A.9b in Appendix A).[41] Meanwhile, high wages, in combination with more output because of the efficient allocation of capital, increase household consumption (Figure A.9a in Appendix A), and such an improvement in financial markets primarily benefits marginalized individuals, that is , non-HC agents in the model. As a result, one can see the convergence across castes in these economic variables. Similarly in the data, I find that the efficient allocation of credit in some states such as Maharashtra implies high household welfare (i.e., high consumption and assets for LC households; see Figure A.10 in Appendix A).[42]

Figure 6: Finance Development and LC Firms: Model



(a) Acces to Credit-LC (b) ARPK (c) Capital Intensity

[41]In this model, households consist of a single agent.
[42]In the data, the household assets represent household possessions and housing.

6.4 Counterfactual Analysis

In the last section, I evaluated how firm performance increases for non-HC individuals over regional financial development. Moreover, I documented that overall economic performance, in terms of output and consumption per capita, improves as states' financial markets perform better. Therefore, it would be interesting to evaluate by how much economic welfare will improve if every state in India efficiently allocates credit across castes. I answer this question in two different counterfactual calibrations.

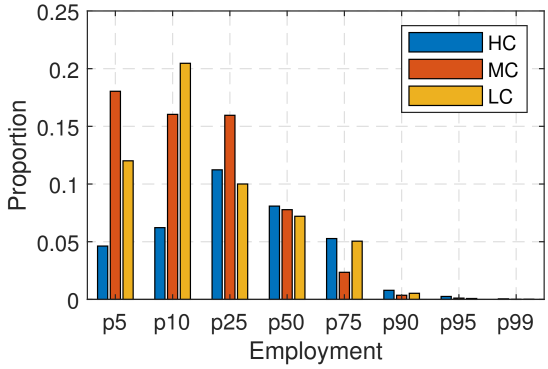
I discussed in Section 6.2 that non-HC individuals differ in terms of fundamentals such as technology and productivity, as well as their respective borrowing capacities. Therefore, in counterfactual analysis $CF1$, I allow the degree of financial frictions for non-HC individuals to be similar to that of HC individuals (i.e., $\lambda_{lc} = \lambda_{mc} = \lambda_{hc}$) and in the second counterfactual exercise $CF2$, along with symmetric access to credit, I enforce the same fundamentals for all castes. The model predicts TFP gains of 6% in $CF1$ and an additional gain of 4% in $CF2$ (see Table 7).

These gains come from two main sources in $CF1$: first, the reallocation of capital from unproductive HC entrepreneurs to more productive non-HC entrepreneurs increases the allocative efficiency of the economy; therefore, as a result, dispersion in $arpk$ declines by 13% and output per capita increases by 8%. Moreover, the economy becomes more capital intensive, with gains of +7%. These gains mostly come from LC and MC entrepreneurs, which increase their capital-labor ratio by 15% and 13%, respectively. Second, the reduction in borrowing constraints induces the entry of more non-HC entrepreneurs. The share of LC enterprises increases from 16% in the benchmark economy to 29%, whereas the share of MC entrepreneurs decreases from 42% to 35% - that is, exactly proportional to their respective population weights. Moreover, because of the excess entry of entrepreneurs, demand for capital and labor increases. This implies a 47% higher interest rate in $CF1$, which further led to the exit of unproductive HC firms. The labor productivity gains for non-HC firms, as mentioned in Table 7, are driven by increments in wages.

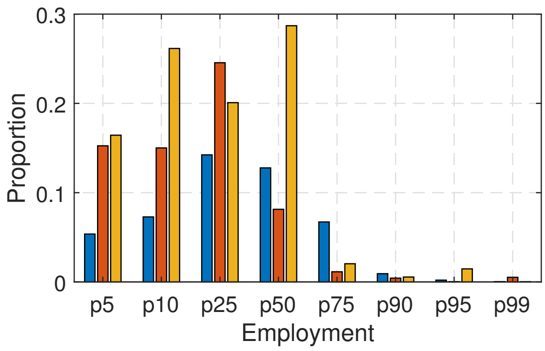
In the $CF2$ economy I allow the span-of-control parameter and productivity distribution to be same for all castes (see Table A.7 in Appendix A for a full characterization of the parametric values). This economy experiences gains of 15% in output per capita and 13% in capital intensity, where most of these gains are driven by the improved performance of non-HC entrepreneurs (see column three of Table 7). In this economy, the gains come from three sources: (i) improved allocation of capital at the intensive margin; (ii) improved selection of entrepreneurs at the extensive margin; (iii) a large span-of-control and improved productivity distribution, which allows non-HC firms to operate on a larger scale and earn higher profits relative to the benchmark economy. The evolution of the employment distribution of three castes over three different economies is shown in Figure 7. It is evident that the employment distribution of non-HC firms is skewed toward the left in the benchmark economy, whereas it shifts toward right in the $CF1$ because of improved credit allocation, while no discernible differences remain in the $CF2$ economy.

Moreover, removing barriers to external financing for non-HC entrepreneurs has distributional consequences. In $CF2$, within caste wealth inequality will increase as non-HC entrepreneurs accumulate more assets; however, cross-caste inequality will decrease. The evidence for this is already provided in Section 6.3, where states with well-functioning financial

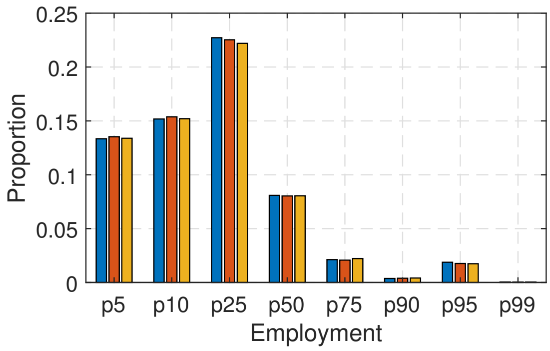
Figure 7: Employment Distribution across Castes: Model



(a) Benchmark economy



(b) CF1



(c) CF2

markets exhibit small differences in their asset holdings.

Finally, I perform two more counterfactual exercises to highlight the importance of misallocation at the extensive and intensive margins and disentangle the gains from these two sources. I start with the stationary distribution $\Lambda(z, a, c)$ in the benchmark economy. I then redistribute capital across entrepreneurs such that $arpk$ equalizes across castes, conditional on their financial wealth and productivity, while the distribution of firms, total capital, and labor supply are kept constant. The reallocation of capital from the unproductive HC entrepreneurs toward non-HC entrepreneurs account for 75% of the total TFP gains.

Next, I allow productive non-HC entrepreneurs to enter the market, along with an efficient allocation of capital across castes. These entrepreneurs could not produce profitably before because of stringent financial frictions. In the new steady state, firms as a proportion of population increase by 14%, while labor supply decreases. This, in conjunction with the enhanced borrowing capacity of non-HC firms, creates more demand for capital and labor, thereby increasing factor prices and further improving the selection of entrepreneurs. The TFP gains from removing talent misallocation at the extensive margin represents 25% of the total gains.

Hsieh and Klenow (2009) argue that if capital and labor were efficiently allocated in India, then TFP would be around 40%-60% higher in the manufacturing sector. Therefore, I conclude that caste-specific distortions in India are important and could account for 15% of the overall gains mentioned in their paper. These results suggest that special attention is needed from

Table 7: Gains in the Counterfactual Economy

	CF1 (%)	CF2 (%)
Overall Economy		
TFP	+6	+10
$\sigma(arpk)$	−13	−13
$Capital\text{-}Intensity$	+7	+13
$Output\text{-}per\text{-}worker$	+8	+15
LC		
$Capital\text{-}Intensity$	+15	+22
$Output\text{-}per\text{-}worker$	+2	+10
$\%\text{-}of\text{-}firms$	+87	+81
MC		
$Capital\text{-}Intensity$	+13	+20
$Output\text{-}per\text{-}worker$	+2	+10
$\%\ of\ firms$	−17	−17

policymakers to unleash the entrepreneurial prowess of non-HC individuals, which not only is important from a social justice point of view but also is an economically efficient thing to do. However, caste-specific distortions are not the whole story as far as misallocation in India is concerned. Potentially, other firm-level distortions are present in the Indian economy that drag productivity growth.

7 Discussion and Robustness

In the last section, I have discussed potential TFP losses due to *arpk* dispersion across castes in the context of the model. Some aspects, however, such as imperfect competition and the heterogeneous output elasticity of capital, are not covered in the model. Therefore, in this section, I discuss the potential impact of these forces on the validity of the results presented in Section 6 and provide further robustness checks.

7.1 Markup Dispersion

The model assumes perfect competition in the goods market, which does not allow me to consider product market distortion, which is potentially correlated with *arpk* dispersion across castes. In principle, markup dispersion could be driven by financial frictions. For example, Chevalier and Scharfstein (1996) and Gilchrist et al. (2017) document a positive correlation between financial constraints and firm markups in times of low demand. In such a situation, the TFP losses mentioned in Table 7 are well identified. Furthermore, recent literature on markups, such as De Loecker et al. (2016), documents increasing markups over firm size. Given the fact that LC firms are small in size, the markups should downwardly bias my estimates of *arpk* differences across castes. However, forces such as selection could drive up the markup for non-HC firms.[43] In what follows, I provide two different pieces of evidence to support my

[43] Other frictions such as demand segmentation in the presence of imperfect competition generate markup dispersion (Goraya and Ilango 2020).

assumption in the baseline model. First, I compute the markups for each caste and include them as controls in the regression model presented in equation 1. Second, I compute a quantity based measure of average products that does not include the selling price of the goods produced.

7.1.1 Markup Estimation

The markup estimation requires a generalized production function, where the firm produces quantity $Q = AK^{\theta_k}L^{\theta_l}M^{\theta_v}$. The variable A is productivity, K is capital, L is labor, and M is intermediate input. The output elasticities of capital, labor, and material input are denoted by θ_k, θ_l, θ_m, respectively. This production function is different from the one assumed in Section 5 in one key aspects: output is in the quantity of the product produced rather than in value-added. Following the seminal paper on markup estimation by **?**, I compute firm markups as

$$Markup = \theta_v \frac{sales}{Variable\,cost}, \tag{8}$$

where θ_v is the sales elasticity of variable input and *variable cost* is the cost of materials. A full characterization of the markup estimation is provided in Appendix A.6. The output elasticity of materials is computed for each caste at the 4-digit sector classification (see Figure A.11).[44] I use the regression specification in equation 1, with firm-level markup μ as an additional control variable. The markup μ is positively correlated with $arpk$;[45] however, it has a negligible effect on caste dummies, particularly in the case of the manufacturing sector (see specifications 3 and 4 in Table 8). Further, the $arpk$ differences presented here are remarkably close to the ones identified in the model (see Section 6), which reinforces the validity of the results presented above.

Table 8: ARPK and Markups

	All sectors		Manufacturing	
	(1)	(2)	(3)	(4)
Dep. Var.	$arpk$	$arpk$	$arpk$	$arpk$
MC	0.0728	0.0657	0.117	0.114
	(0.036)	(0.036)	(0.047)	(0.046)
LC	0.151	0.132	0.201	0.190
	(0.074)	(0.071)	(0.058)	(0.057)
μ		0.0759		0.0448
		(0.026)		(0.034)
Obs (millions)	1.4	1.4	1.0	1.0
R-squared	0.154	0.158	0.170	0.172
State & NIC4 FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓

Notes: Results from firm-level regression, presented in equation 1. Sector and state fixed effects are included. Sampling weights are applied. Standard errors are in parentheses.

[44]The output elasticity of material input is evaluated using cost-share methodology. This approach requires a constant returns to scale assumption for the production technology.

[45]The $arpk$ measure is based on gross-output as well to be consistent with the model of markup estimation.

7.1.2 Measuring Average Product of Capital

In this paper I rely on a revenue based measure of average products, which includes firm-level prices. Here, I exploit one more dimension of the data to compute a quantity-based measure of average products for enterprises that produce only one product.[46] The average product of capital, apk, is defined as follows:

$$apk_{isc} := \ ln(APK_{isc}) = ln(Q_{isc}) - ln(K_{isc}).$$

I exploit the regression model in equation 1 with product-level fixed effects. The apk for LC and MC firms is 40% and 24% higher than that of HC firms (see Table 9). These estimates are larger than those observed while using $arpk$.

Table 9: Average Product of Capital

Dep. Var.	All-Sectors apk	Manufacturing apk
MC	0.280	0.236
	(0.094)	(0.119)
LC	0.407	0.400
	(0.119)	(0.165)
Obs.	97,913	87,184
R-squared	0.553	0.383
State & Product FE	✓	✓
Controls	✓	✓

Notes: Results from firm-level regression, presented in equation 1. Dependent variable is average product of capital. The product and state fixed-effects are included. The sampling weights are applied and standard error are in parentheses.

7.1.3 Output Elasticity of Capital

Using the framework from the previous section, I am able to compute the output elasticity of capital θ^k for each caste within a sector. In Figure A.12 in Appendix A, I compared the values of θ^k for LC and MC firms against those of HC firms and found no systematic bias.

Further, $arpk$ in this framework can be decomposed as follows;

$$arpk_{isc} = \mu_{isc} - \hat{\theta}^k_{sc} + \tau_{isc} + constant,$$

where μ_{isc} is firm-level markup as defined above, $\hat{\theta}^k_{sc}$ is log of output elasticity of capital, and τ_{isc} is firm-level distortions. For example, in the presence of only financial frictions, it represents the Lagrange multiplier, which increases as the firm becomes more constrained. The decomposition pins down a negative relation between $arpk$ and the output elasticity of capital; that is, those who use capital-intensive technologies should have a lower $arpk$, all else equal. Under the assumption that $\hat{\theta}^k_{sc}$ is not correlated with τ_{isc}, I control for the output elasticity of

[46] I use single product firms because the data are not detailed enough to compute apk for multi-product firms. In particular, the measure of capital and labor is at the firm level and not at the product level.

capital using the regression model mentioned in equation 1.[47] I find no effect on the estimates of LC dummy but document negative effects on estimates of the MC dummy (see Table A.8 in Appendix A).

8 Conclusion

It is well established that misallocation of resources can explain a large chunk of productivity differences across countries. However, its sources are still disputable and several firm-level distortions and frictions have been proposed. This paper suggests that the caste system in India is one example of such distortions and quantifies its importance in explaining aggregate TFP losses, as mentioned in Hsieh and Klenow (2009).

This paper takes a different perspective in dissecting firm-level data in India. Instead of using firm performance measures, I use the caste of the firm owner as a defining feature. I document a large dispersion in $arpk$ across firms of different castes, whereas no such dispersion is visible for $arpl$. Further, contrary to the previous literature that documents a high $arpk$ for large firms in India, I find that firms owned by historically disadvantaged castes while small in size, exhibit a high $arpk$.

I then use a quantitative model of entrepreneurship, based on Buera and Shin (2013), to decompose the effects of fundamentals such as productivity and technology, as well as the availability of external financing, on the cross-caste $arpk$ dispersion. The model identifies a very high degree of financial constraints for non-HC entrepreneurs. Meanwhile, the productivity distribution is characterized by a lower dispersion, and the scale of production technology is smaller for LC and MC individuals relative to HC individuals.

In this paper, I exploit the heterogeneity in financial development across various states in India to identify the impact of limited access to credit on the performance of firms owned by non-HC agents and its overall welfare implications for the non-HC population. The $arpk$ difference vanishes over regional financial development. Meanwhile, the welfare of non-HC individuals increases substantially; in particular, household consumption and asset holdings converge toward the level of HC individuals.

I use the model to perform various counterfactual experiments. First, I homogenize the degree of financial frictions across castes, which delivers TFP gains of 6%. Second, an additional 4% of TFP gains are realized when I impose the productivity process and technology of HC individuals on that of non-HC individuals. In the counterfactual economy, gains come from three sources. The first source is the improved allocation of capital across castes at the intensive margin. The second is the improved selection of entrepreneurs at the extensive margin, particularly the entry of productive but poor non-HC entrepreneurs and the exit of unproductive but wealthy HC entrepreneurs. The third source is the use of large scale production technology and an improved productivity distribution, which allows non-HC firms to operate at a larger scale and earn higher profits relative to the benchmark economy.

Given the findings of this paper, a natural next step would be to understand the implication of the caste system on long-run growth. Furthermore, understanding the causes of productivity and technological differences across castes is important for establishing well-guided policies and therefore is a promising avenue for future research.

[47] In models of technology adoption in the presence of financial frictions, this assumption breaks down, and therefore the estimates of caste-dummies in Table A.8 in Appendix A will be biased downward.

References

Acemoglu, D. and Robinson, J. A. (2019). *The narrow corridor: States, societies, and the fate of liberty*. Penguin Press.

Alesina, A. and Ferrara, E. L. (2005). Ethnic diversity and economic performance. *Journal of Economic Literature*, 43(3):762–800.

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

Asturias, J., García-Santana, M., and Ramos, R. (2019). Competition and the welfare gains from transportation infrastructure: Evidence from the golden quadrilateral of india. *Journal of the European Economic Association*, 17(6):1881–1940.

Ayyagari, M., Demirguc-Kunt, A., and Maksimovic, V. (2014). Does local financial development matter for firm lifecycle in india? *The World Bank*.

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

Banerjee, A. V. and Duflo, E. (2005). Growth theory through the lens of development economics. *Handbook of Economic Growth*, 1:473–552.

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

Bellemare, M. F., Barrett, C. B., and Just, D. R. (2013). The welfare impacts of commodity price volatility: evidence from rural ethiopia. *American Journal of Agricultural Economics*, 95(4):877–899.

Bidner, C. and Eswaran, M. (2015). A gender-based theory of the origin of the caste system of india. *Journal of Development Economics*, 114:142–158.

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

Buera, F. J., Kaboski, J. P., and Shin, Y. (2015). Entrepreneurship and financial frictions: A macrodevelopment perspective. *Annual Reviews of Economics*, 7(1):409–436.

Buera, F. J. and Shin, Y. (2013). Financial frictions and the persistence of history: A quantitative exploration. *Journal of Political Economy*, 121(2):221–272.

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

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

Chevalier, J. A. and Scharfstein, D. S. (1996). Capital market imperfections and countercyclical markups: Theory and evidence. Technical Report 4.

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

De Loecker, J., Goldberg, P. K., Khandelwal, A. K., and Pavcnik, N. (2016). Prices, markups, and trade reform. *Econometrica*, 84(2):445–510.

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

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

Deshpande, A., Sharma, S., et al. (2013). Entrepreneurship or survival? caste and gender of small business in india. Technical report, Centre for Development Economics Department of Economics, Delhi School of Economics.

Deshpande, M. S. (2010). History of the indian caste system and its impact on india today.

Easterly, W. and Levine, R. (1997). Africa's growth tragedy: policies and ethnic divisions. *The Quarterly Journal of Economics*, 112(4):1203–1250.

Erosa, A., Fuster, L., Kambourov, G., and Rogerson, R. (2017). Hours, occupations, and gender differences in labor market outcomes. *NBER Working Paper*, (w23636).

Fehr, E. and Hoff, K. (2011). Tastes, castes and culture: The influence of society on preferences. *The Economic Journal*, 121(556):F396–F412.

Fisman, R., Paravisini, D., and Vig, V. (2017). Cultural proximity and loan outcomes. *American Economic Review*, 107(2):457–92.

Foster, L., Haltiwanger, J., and Syverson, C. (2008). Reallocation, firm turnover, and efficiency: selection on productivity or profitability? *The American Economic Review*, 98(1):394–425.

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

Gilchrist, S., Schoenle, R., Sim, J., and Zakrajšek, E. (2017). Inflation dynamics during the financial crisis. *American Economic Review*, 107(3):785–823.

Goraya, S. and Ilango, A. (2020). Demand segmentation and markups. *Mimeo*.

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

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

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

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

Hoff, K. and Pandey, P. (2006). Discrimination, social identity, and durable inequalities. *The American Economic Review*, 96(2):206–211.

Hopenhayn, H. A. (2014). Firms, misallocation, and aggregate productivity: a review. *Annual Review of Economics*, 6(1):735–770.

Hsieh, C.-T., Hurst, E., Jones, C. I., and Klenow, P. J. (2019). The allocation of talent and us economic growth. *Econometrica*, 87(5):1439–1474.

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

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

Iyer, L., Khanna, T., and Varshney, A. (2013). Caste and entrepreneurship in india. *Economic and Political Weekly*, 48(6):52–60.

Jodhka, S. S. (2004). Sikhism and the caste question: Dalits and their politics in contemporary punjab. *Contributions to Indian sociology*, 38(1-2):165–192.

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

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

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

Montalvo, J. G. and Reynal-Querol, M. (2005). Ethnic diversity and economic development. *Journal of Development Economics*, 76(2):293–323.

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

Neuman, D. M. (1981). Caste and social stratification among muslims in india. *The Journal of Asian Studies*, 40(2):400–402.

Puri, H. K. (2003). Scheduled castes in sikh community: A historical perspective. *Economic and political weekly*, pages 2693–2701.

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

Thorat, S. and Sadana, N. (2009). Caste and ownership of private enterprises. *Economic and Political Weekly*, pages 13–16.

Villanger, E. (2015). Entrepreneurial abilities and barriers to microenterprise growth: A case study in nepal. *The Journal of Entrepreneurship*, 24(2):115–147.

A Data Appendix

A.1 MSME Dataset

The MSME census is based on MSME sector which is defined by the Micro, Small and Medium Enterprise Developmemt (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 41% of the manufacturing output and 40% of the total exports of the country.[48] 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 (HC) own and operate 2.9 (11 %), 10.4 (40 %) and 11.4 (44 %) million MSMEs.

Unlike ASI and Prowess datasets, the economic census and the MSME datasets are able to capture small enterprises that are more likely to face financially 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.

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 the cost of capital interest rate and assumed to be 5.682%. 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. Such evidence suggests that very selected low-caste agents are entering the market.

A.2 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

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

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 (HC).[49]

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 A.2 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.

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 HC 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 HC 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.

A.3 ASI-NSS 2006

The firm-level dataset for the manufacturing sector India is provided by Annual Survey of Industries(ASI),which covers registered manufacturing. However, this dataset does not include small firms or unregistered firms. In particular, according to India's Factories Act of 1948 as explained in Section 3, establishment with more than 10 workers, in case they use electricity and 20 workers, in case they do not use electricity are required to registered. Hence, the ASI provides a truncated size distribution. I use National Sample Survey (NSS) 2006, which covers production units in the unorganized sector in India. The employment distribution is provided in table A.5.

A.4 Household Surveys 2005 & 2012

IHDS surveys are household surveys that includes information on consumption, assets, wages, business-income, Desai et al. (2018). The Income distribution is provided in table A.6.

[49]Following Iyer et al. (2013), I keep 19 large states of India that constitute 95 % of all the enterprises and 96 % of the population.The 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.

A.5 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. Furthermore, the variables used in regressions $arpk$, $arpl$, $tfpr$, k/l are winsorized at 1 and 99th percentile.

A.6 Markup Estimation

Consider the following cost minimization problem;

$$\begin{aligned} &\min_{K,LM} \; RK + wL + P^m M + \kappa \\ \text{s.t.} \quad & Q = AK^{\theta_k} L^{\theta_l} M^{\theta_v}, \; and \; \sum_j \theta_j = 1, \end{aligned} \tag{9}$$

where, Q is quantity produced, K is capital, L is labor, M is intermediate input. Further, total cost for firm is composed cost of capital RK, where R cost of capital and assumed to be $r + \delta$, i is the interest rate and δ is the depreciation rate; wL is wage-bill; $P^m M$ cost of materials with P_m being firm-specific purchasing price; and κ is fixed cost of operating. The markup estimation does not require cosntant returns o scale assumption, however, it is necessary to estimate output elasticities as discussed below.[50]

Further, it is assumed that capital K is chosen in the presence of frictions, including markups; and material and labor choices are undistorted except for the markup.[51] The markup can be computed, using cost of any input, as long as it is not fixed. Therefore, I use material input as labor and capital are quasi-fixed in the Indian context.

The first order conditions form cost minimization problem defined above gives me markup μ_{isc}, of firm i in sector s with owner of caste c that is equal to;

$$\mu_{isc} = \theta^v_{sc} \frac{P_{isc} Q_{isc}}{P^m_{isc} M_{isc}} \tag{10}$$

I use cost share technique to compute elasticities, see Foster et al. (2008). This technique requires all inputs to be free, however averaging out across the sample can get rid of this concern. Moreover, one need to specify cost of capital. I use $r = 0.0568$ and $\delta = 0.06$. Finally, it requires constant returns to scale technology. The cost share is;

$$\theta^v_{isc} = \frac{P^m_{isc} M_{isc}}{P_{isc} M_{isc} + wL_{isc} + RK_{isc}} \tag{11}$$

The sectoral output elasticities of material inputs are computed as $\theta^v_{sc} = median_{i \in s}\{\theta_{isc}\}$. The comparison of θ^v_{sc} across caste is presented in figure A.11. No systematic bias is evident from the respective estimates. The $arpk$, in this setting, is defined as;

$$arpk_{isc} := \; ln(ARPK_{isc}) = ln(P_{isc} Q_{isc}) - ln(K_{isc}).$$

Figure A.1: The Caste System

[50] Other popular approches that are available to estimate output elasticities demand panel data.

[51] This method allows for any distortion in the input market.

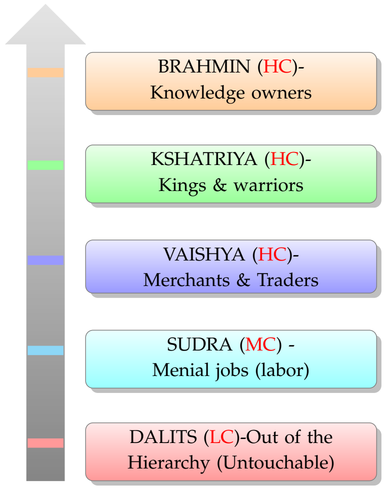
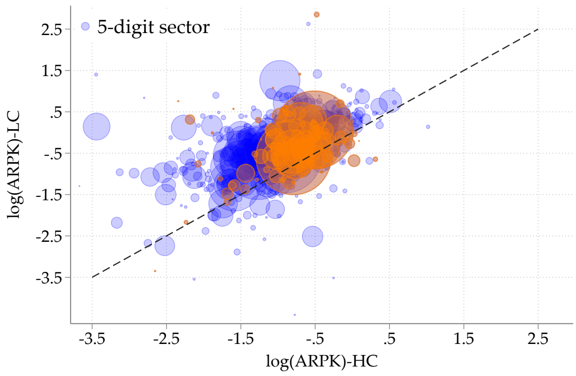
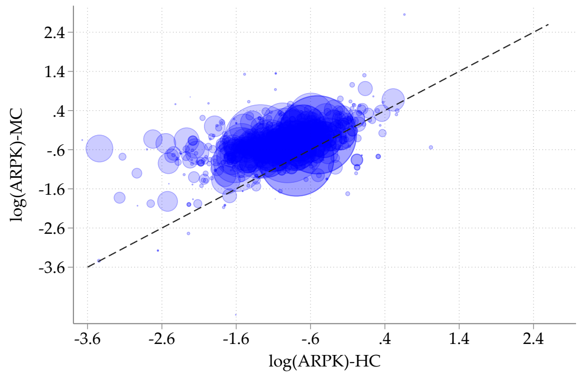


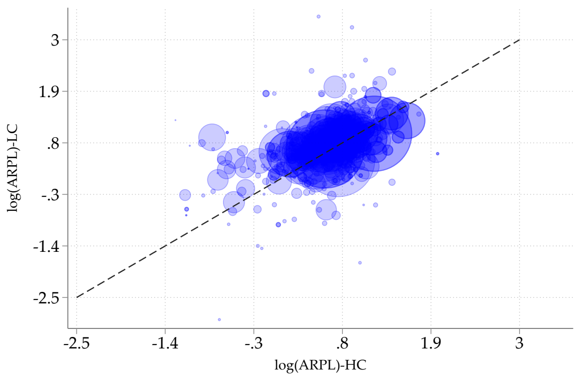
Figure A.2: ARPK & ARPL: Data



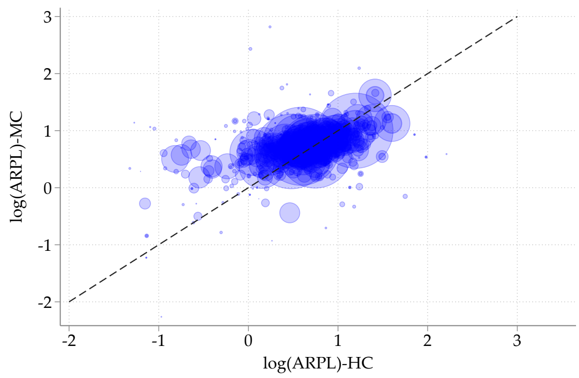
(a) ARPK-LC



(b) ARPK-MC



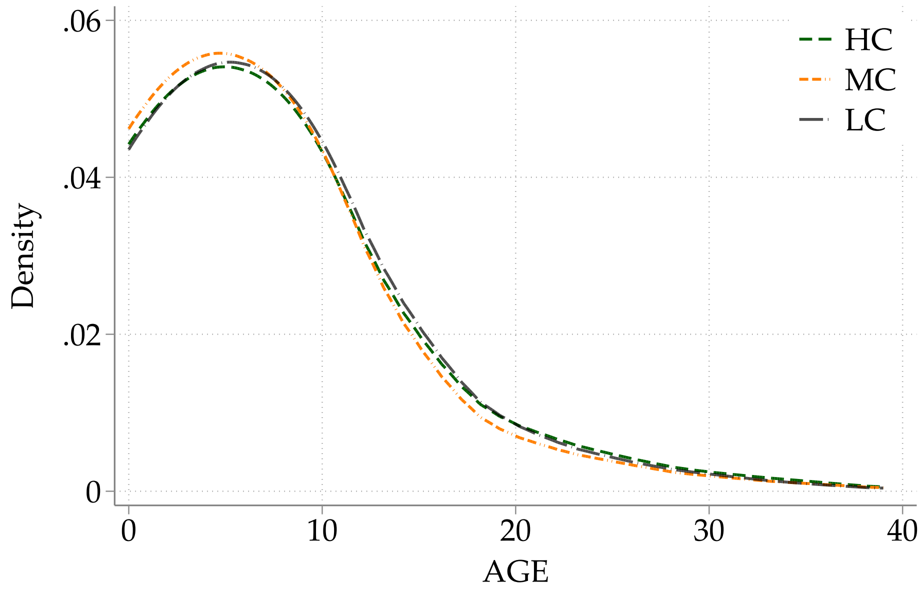
(c) ARPL-LC



(d) ARPL-MC

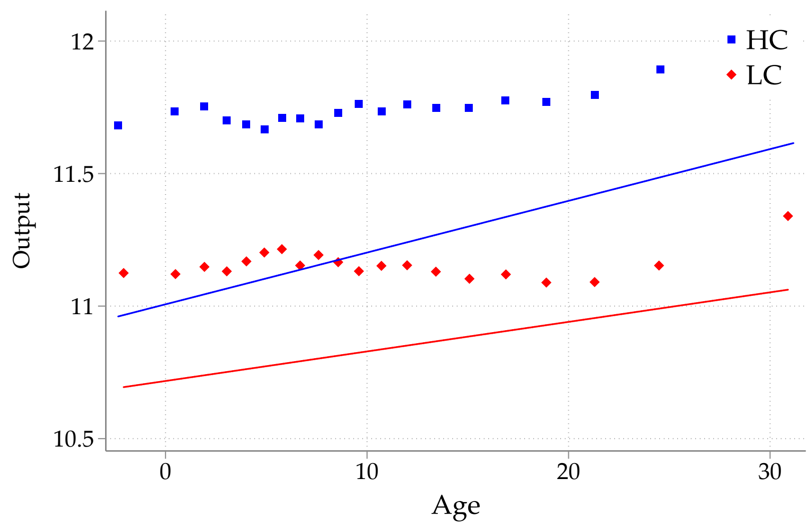
Note. Each blue circle represents a 5 digit sector (633 in total). The orange circles represent sectors such as food products and beverages (NIC-15), tanning and dressing of leather; manufacture of luggage, handbags, saddlery, harness and footwear, apparels or furniture (NIC-18,19). Sampling weights are applied.

Figure A.3: Age Distribution



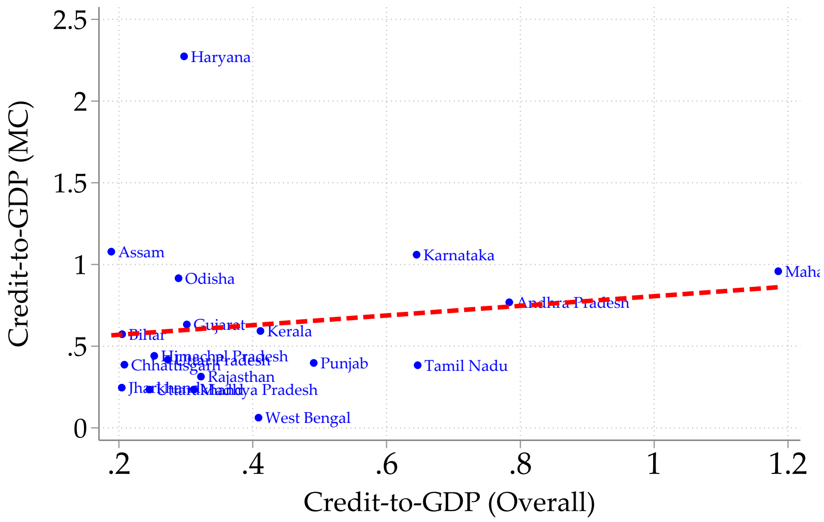
Note. sampling weights applied.

Figure A.4: Output and Age: Data



Notes: Binscatter plot with age on x-axis and output on y-axis. Each square and diamond represent mean of the x-axis and y-axis variables within equally-sized bin of variable in x-axis for HC and LC firms, respectively. Sector and state FE included. sampling weights applied.

Figure A.5: Regional Financial Development-Data



Notes: The overall credit-to-GDP ratio is computed with statistics published by the Reserve Bank of India. The credit-to-GDP ratio for MC firms is computed in MSME data. Sampling weights are applied

Figure A.6: Finance and TFPR: Model

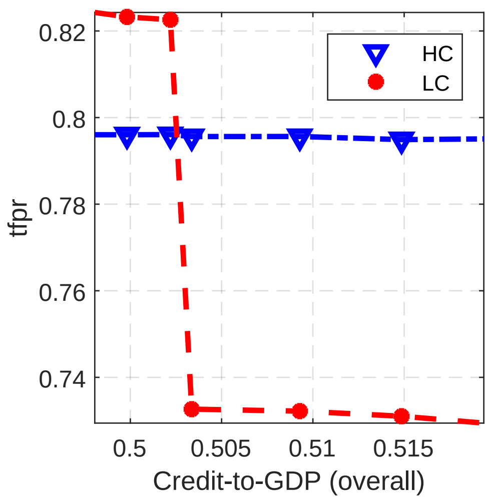
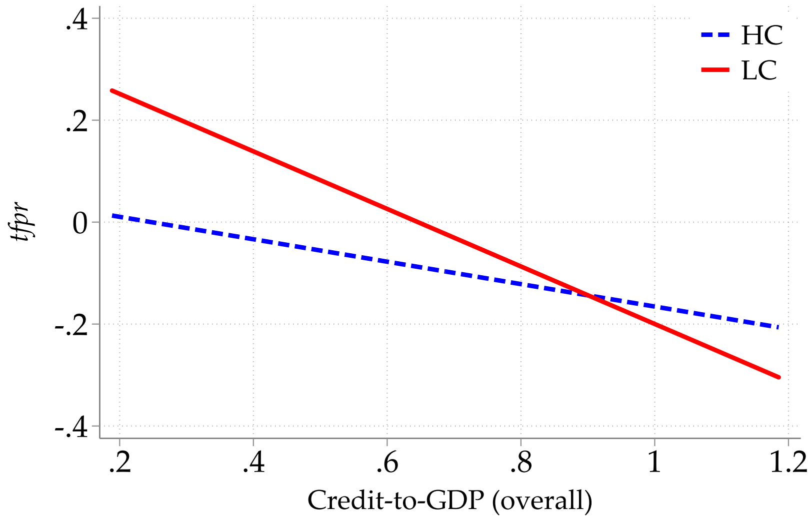
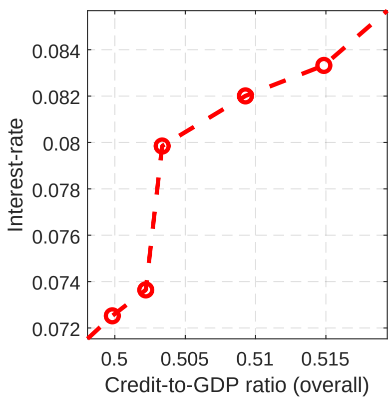


Figure A.7: Finance and TFPR: Data

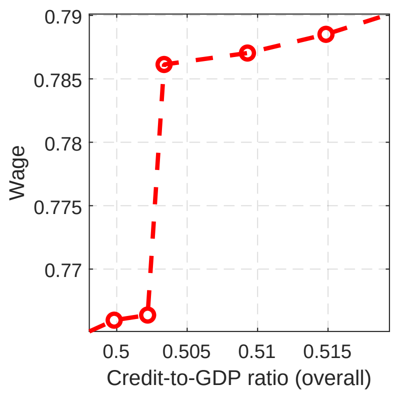


Notes: Linear-regression fit plot with credit-to-output ratio on x-axis and $tfpr$ on y-axis. Sector and state FE included. sampling weights applied.

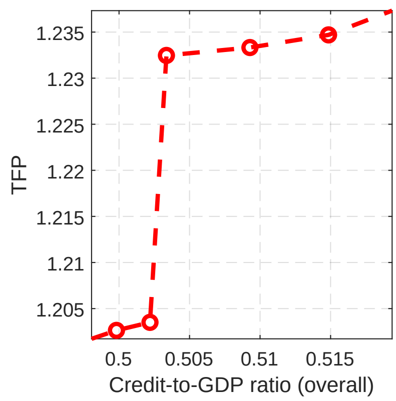
Figure A.8: Finance and Regional Development-Model



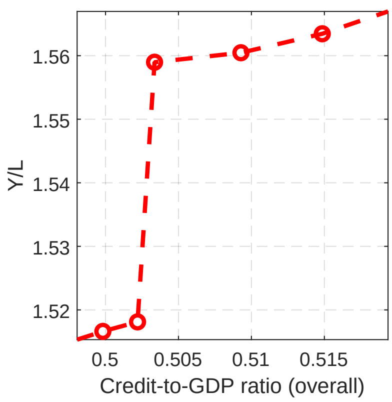
(a) Interest-Rate



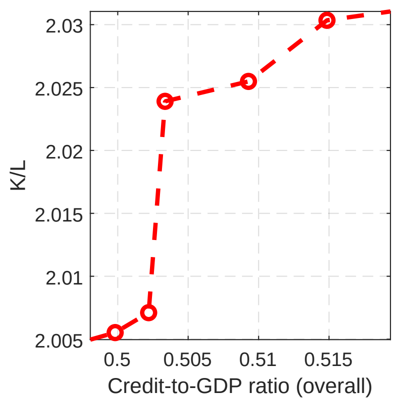
(b) Wages



(c) TFP

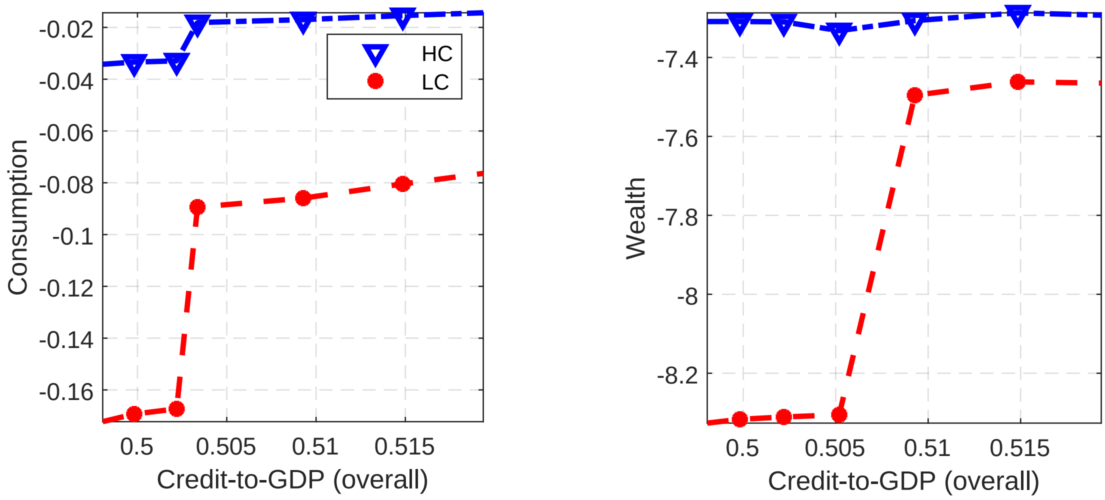


(d) GDP-per-Capita



(e) Capital-Intensity

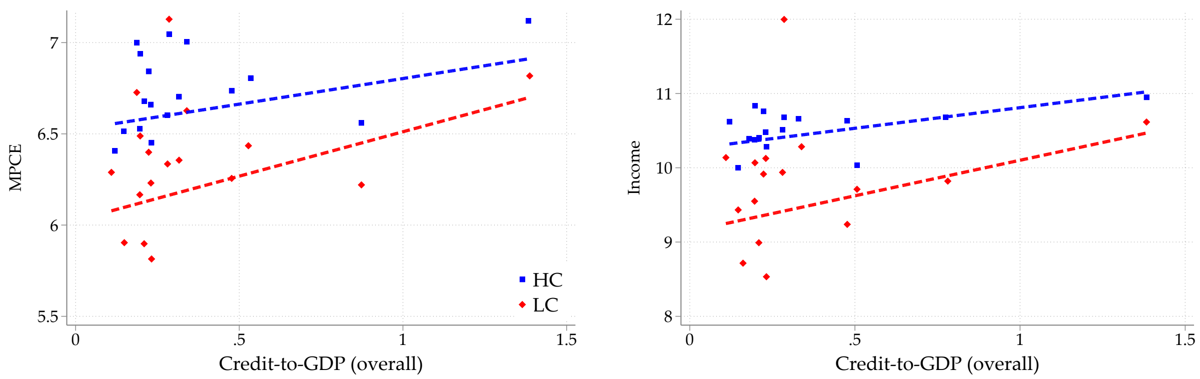
Figure A.9: Financial Development & LC Households-Model



(a) Comsumption (b) Financial Wealth

Note. Coefficients of the low caste dummy from regressions of log(k/l) (column 1) and log(MRPK) (column) using specification 2 and 5 in Table **??** for each age bin on the X-axis. Rows represent the employment bins.

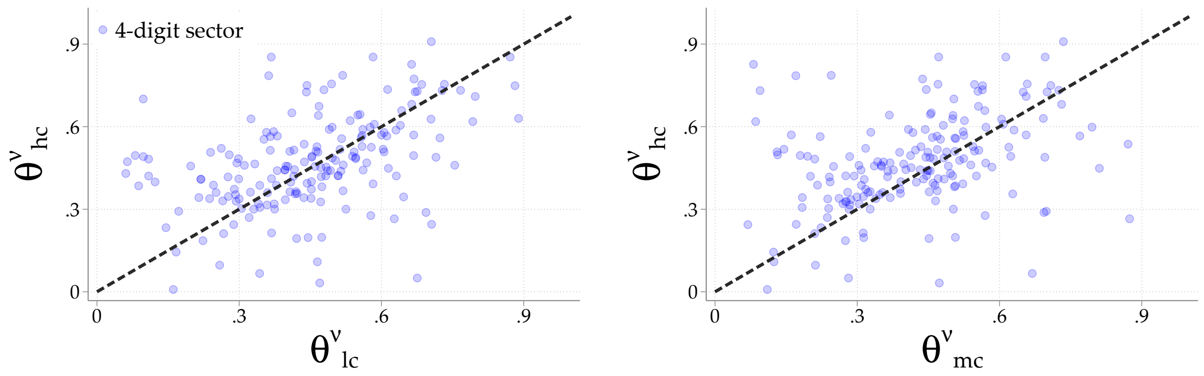
Figure A.10: Financial Development & LC Households-Data



(a) Per-capita Comsumption (b) Household Assets

Notes: Binscatter plot with credit-to-output ratio on x-axis and y-axis; (a) MPCE and (b) Household Assets . Each square and diamond represent mean of the x-axis and y-axis variables within equally-sized bin of variable in x-axis for HC and LC firms, respectively. sampling weights applied.

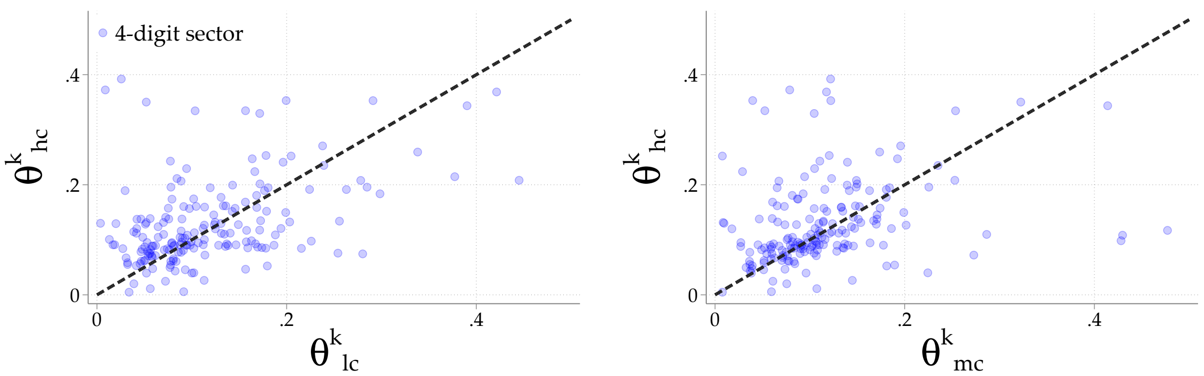
Figure A.11: Output elasticity of Variable Input-Data



(a) LC (b) MC

Note. Each blue dot represent a 4-digit sector. θ^{ν} is the output elasticity of material input. The respective subscripts represent caste. Sampling weights applied.

Figure A.12: Output elasticity of Capital-Data



(a) LC (b) MC

Note. Each blue dot represent a 4-digit sector. θ^{k} is the output elasticity of capital input. The respective subscripts represent caste. Sampling weights applied.

Table A.1: $arpk$ and Financial Development

VARIABLES	(1) HC	(2) MC	(3) LC
Fd_s	-0.0746	-0.411	-0.759
	(0.153)	(0.099)	(0.152)
Constant	-0.0563	0.261	0.598
	(0.075)	(0.049)	(0.061)
Observations	719,313	547,316	134,561
R-squared	0.101	0.101	0.135
Control	✓	✓	✓
SIC3 FE	✓	✓	✓

Notes: Results from the enterprise level regression. Dependent variables are in logs and shown in column headings. Fd is index of financial development across states. The vector of controls, Γ, that includes region, gender and religion FE. Robust standard errors in parentheses. Clustered at sector level. Sampling weights are applied.

Table A.2: Share of Population and Non-agricultural Enterprises across castes

	(1)	(2)	(3)	(4)	(5)
			Enterprises with		
Caste	Population	Enterprises	One employee	Outside labor	Employment
LC	29%	13%	14%	10%	11%
MC	35%	43%	44%	10%	39%
HC	36%	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 IHDS 2005 survey. Outside labor means labor outside the household.

Table A.3: $arpk$ in Manufacturing Sector: Data

Dep. Var.	(1) $arpk$	(2) k/l	(3) $tfpr$
MC	0.223	-0.313	0.239
	(0.054)	(0.060)	(0.042)
LC	0.340	-0.582	0.245
	(0.073)	(0.081)	(0.069)
Constant	-0.173	10.54	2.926
	(0.030)	(0.037)	(0.025)
Observations	975,983	975,983	939,459
R-squared	0.176	0.263	0.115
State FE	✓	✓	✓
NIC4 FE	✓	✓	✓
Controls	✓	✓	✓

Notes: Results from the enterprise level regression using equation 1 and 2. Dependent variables are in logs and shown in column headings. $arpk$ and $arpl$ are average products of capital and labor, respectively. M-caste is the dummy variable for the middle-caste enterprises. L-caste is the dummy variable for the low-caste enterprises. The vector of controls, Γ, that includes region, gender and religion FE. Robust standard errors in parentheses. Clustered at Caste, region and sector level. Sampling weights are applied.

Table A.4: Employment Distribution-Economic Census 2005

Firms	p50 (%)	p75 (%)	p90 (%)	p95 (%)	p99 (%)
All	0.36	0.36	0.53	0.64	0.74
HC	0.24	0.32	0.48	0.56	0.68
MC	0.21	0.45	0.63	0.72	0.81
LC	0.23	0.54	0.66	0.78	0.86

Table A.5: Employment Distribution-ASI & NSS 2006

Firms	p50 (%)	p75 (%)	p90 (%)	p95 (%)	p99 (%)
All	0.42	0.42	0.60	0.64	0.76

Table A.6: Income Distribution-Economic Census 2005

Firms	p50 (%)	p75 (%)	p90 (%)	p95 (%)
IHDS 2005				
All	0.13	0.33	0.55	0.68
HC	0.17	0.36	0.56	0.68
MC	0.14	0.36	0.60	0.71
LC	0.13	0.34	0.61	0.72
IHDS 2012				
All	0.13	0.31	0.50	0.63
HC	0.12	0.29	0.49	0.60
MC	0.14	0.33	0.55	0.65
LC	0.15	0.37	0.63	0.73

Table A.7: Parameter Values

Parameter	BM-Value	CF1-Value	CF2 -Value	Description
Fixed:				
δ	0.060	0.060	0.060	Annual depreciation rate physical capital
α	0.330	0.330	0.330	Physical capital share
γ	1.500	1.500	1.500	Coefficient of risk aversion
ρ	0.844	0.844	0.844	Discount factor
Fitted:				
$1-\nu_h$	0.761	0.761	0.761	Span of control for HC
$1-\nu_m$	0.745	0.745	0.761	Span of control for MC
$1-\nu_l$	0.745	0.745	0.761	Span of control for LC
ψ_h	0.927	0.927	0.927	Persistence in productivity for HC
ψ_m	0.922	0.922	0.927	Persistence in productivity for MC
ψ_l	0.918	0.918	0.927	Persistence in productivity for LC
λ_h	1.760	1.760	1.760	Degree of financial frictions for HC
λ_m	1.370	1.760	1.760	Degree of financial frictions for MC
λ_l	1.160	1.760	1.760	Degree of financial frictions for LC
η_h	4.520	4.520	4.520	Scale parameter of ability distribution for HC
η_m	4.700	4.700	4.520	Scale parameter of ability distribution for MC
η_l	4.890	4.890	4.520	Scale parameter of ability distribution for LC
c_f	0.100	0.100	0.100	Fixed cost of Operation

Table A.8: ARPK and Markups

	All sectors			Manufacturing		
Dep. Var.	$arpk$	$arpk$	$arpk$	$arpk$	$arpk$	$arpk$
MC	0.0728	0.0674	0.0349	0.117	0.115	0.0779
	(0.036)	(0.036)	(0.038)	(0.047)	(0.047)	(0.046)
LC	0.151	0.132	0.189	0.201	0.188	0.204
	(0.074)	(0.071)	(0.061)	(0.058)	(0.057)	(0.056)
mu		0.0769	0.0785		0.0463	0.0477
		(0.026)	(0.026)		(0.034)	(0.034)
θ^k_{sc}			-2.886			-3.615
			(0.912)			(0.978)
Constant	0.453	0.418	0.762	0.477	0.459	0.839
	(0.026)	(0.029)	(0.116)	(0.026)	(0.029)	(0.105)
Obs (millions)	1.4	1.4	1.4	1.0	1.0	1.0
R-squared	0.154	0.158	0.162	0.170	0.172	0.176
State & NIC4 FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓

Notes: Results from firm-level regression, presented in 1. Sector and state fixed-effects are included. Sampling weights applied. Standard error in parentheses.