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DO others matter? AN EMPIRICAL ANALYSIS OF THE INTERACTION OF SOCIAL AND HUMAN CAPITAL IN INDIA

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Introduction
There is nothing controversial in saying that human capital matters a great deal for economic development. Research during the past 50 years has confirmed this belief, and governments, international organizations and NGOs have worked hard to improve human capital indicators. The Millennium Development Goals, which aimed at eradicating poverty by 2015, are a good example of this increased interest: four out of the eight goals are directly or indirectly concerned with human capital.

The majority of policy makers and researchers have considered and studied human capital as an issue only concerning individuals. On the policy side, investing in human capital is seen as an effective way of decreasing poverty because it opens up new opportunities to individuals. On the research side, the huge literature on the private returns to human capital is an example of this focus. However, human capital also has a social component which has not yet been well understood, despite a growing literature looking beyond the individual aspect of human capital.

The aim of this dissertation is to shed some light on this social component of human capital. The recurrent question that I am asking throughout this thesis is “How do others matter?” in relation to human capital. In particular, I am wondering how social capital interacts with human capital. To study this question, I take India as a case study. India is a country where human capital has dramatically changed in the last 50 years, and social capital had an important role in this evolution. More concretely, India’s peculiar social structure, that is explained in details in the following section, provides a very interesting context to study the relation between human capital and social capital.

Before going further into this introduction, I need to clarify what I mean by human capital and social capital. Human capital is a global term which refers to “the productive capacity of human beings” (Schultz, 1961) and can be increased through investment in “schooling, on-the-job training, medical care, migration” (Becker, 1993). This list is far from being complete, and they are many other ways to invest in human capital, but the literature has mainly focused on these four components of human capital. In this dissertation, the focus is even more...
restrictive: human capital is defined as people’s education level. This is however a common simplification,\(^3\) notably because education is the component of human capital which has the most direct economic impact (for example on wages) but also because it is is easily quantifiable.

Social capital, too, is a complex concept, and there is still a lively debate on how to define it (Hayami, 2009). However, there is a consensus on the fact that social capital is “embodied in relations among persons” (Coleman, 1988). In other words, following Putnam (1995), social capital can be defined as “features of social life -networks, norms, and trust- that enable participants to act together more effectively to pursue shared objectives”. Again here, my focus is not on social capital as a whole, but rather on the network component of social capital. More precisely, in this dissertation, I use the social structure of India, the caste system, to define the social capital to which individuals have access to. Indeed, as it is explained in the first section of this introduction, interactions in India (and especially in rural India) are still mainly happening within castes.

The rest of this introduction is organized as follows. Section 1 first discusses how castes and human capital are related in India, before section 2 provides an overview of the literature on the relation between human capital and social capital. Finally, section 3 presents the outline of this dissertation.

1. **How do social capital and human capital interact in India?**

The caste system is a complicated institution with lots of rules, and getting a clear picture of how it works would require more than this introduction. However, social interactions in India (and therefore this dissertation) cannot be understood without basic knowledge on castes. Therefore, in this section I first explain the essential features of the caste system and the rules which regulate its functioning,\(^4\) before focusing on how castes relate to human capital in India. We will see that the hierarchy in the caste system is a strong predictor of human capital, but this situation is not a dead end, as it is explained in the third subsection, because there is room for castes’ mobility.

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\(^3\)Becker (1993) himself in his seminal work on human capital actually restricts his analysis to education.

\(^4\)For readers who want to know more about castes, a more complete description of the system can be found in Bros (2010).
1.1 The caste system

According to the Hindu religion, the Indian society is divided into four *Varnas*: the Brahmans (priests and teachers), the Kshatriyas (rulers and warriors), the Vaishyas (traders) and the Shudras (servants).

Figure 1: The caste system

The system is often represented as in figure 1, where the position of each Varna in the pyramid represents their hierarchical position. More precisely, Brahmans, Kshatriyas and Vaishyas are considered as high castes. Shudras are low castes, and are hierarchically lower than all the others. Apart from these four groups, there are also people who do not belong to any Varna because their have occupations considered as profane or dirty, such as dust cleaning or scavenging. They are called the Untouchables or Dalits (or Scheduled Castes, this term will be explained later). They are hierarchically at the very bottom of the society.

In practice however, the Indian society is divided in thousands of groups called *jatis*. Each jati relates to a specific Varna and can consequently be situated in the global hierarchy. The jati is the real group of reference in India, along which social life is organized. Each jati has a traditional occupation which often gave its name to the group. For example, the Kurubas in Karnataka are traditionally shepherds, and they derive their name from “Kuri” which means “sheep” in Kannada. The traditional occupation also determines the degree of purity or impurity of each jati, which in turn determines their status compared to the other jatis. Untouchables have very polluting occupations, whereas high castes have purer occupations,
more related to intellectual activities, such as teaching or religious activities. Consequently, high castes can be “polluted” if they are touched by low castes for example or if they share the same food. Interactions and exchanges between jatis have therefore to follow specific rules so that purity can be preserved. Relations between jatis are also governed by other rules, like those of heredity and endogamy. The jati one belongs to is the same as the one of her/his parents, and one has to marry within her/his jati. It is therefore hard to escape one’s jati, and social mobility is strongly dependent on the mobility of the jati as a whole.

So what do we mean when we talk about castes? The term “castes” is often used to refer to the system as a whole, the Varna and the jati system. In this dissertation, the term caste is used in the same way. However, there are some situations where the term caste refers specifically to the Varnas, as in chapter 2 for example, or to jatis, as in chapter 3 and 4. It will be made explicit when it is the case.

One consequence of the caste system, and in particular of the division of labor across castes which restricted in the past low castes to low-skilled jobs, is the creation of a very unequal society, where wealth is divided along caste lines. This situation has been maintained by the discrimination that low castes were and still are facing. However, since Independence, individual socio-economic mobility has increased thanks to urbanization and development, and households often have another activity than the traditional one of their jati. The correlation between caste and economic status is therefore not anymore perfect. So what is the relevance of castes today? Does it make sense to consider that social capital is mainly created within castes in India?

The answer is yes. Scholars agree to say that, although the system has evolved a lot in recent years, caste is still what defines social relations in contemporary India. Indeed, caste identity is very strong and some researchers even claim that it has been strengthened during the 20th century. Dirks (2011) for example argues that the caste system before colonization was not as rigid, and that the British participated in the reinforcement of caste identity because they used the caste system to establish their authority. The censuses that they conducted also played an important role, because people were asked about their caste. Dirks affirms that the official verbalization of people’s identity created a sense of belonging to their caste group. Caste identity has also been accentuated by the affirmative action policies put into place after Independence, for which the eligibility criteria is caste-based. Not only the caste identity of those being eligible has been reinforced, but also the identity of those not eligible, who gathered to oppose the policy, or who

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5 Although we see in section 1.2 that the correlation is still strong.
constituted themselves into pressure groups to get access to the same benefits.

Two examples can illustrate the fact that castes are a very important determinant of social life today. The first example is the development of caste politics: parties where mobilization is based on castes have emerged all over India (Chandra, 2004). The second example is that the rule of endogamy is still enforced. Marriage within the subcaste is still the norm, and there is also anecdotal evidence that intra-caste marriage does not only concern the old generations. For example, matrimonial websites are flourishing in India, and for most of them, declaring the jati is a pre-requisite. Stories about young couples who were killed by their families because they were not from the same caste are also widely spread.

The caste system is very constraining, and its persistence can seem surprising. But one important reason why caste still exists today is that it is also a useful institution for its members. Munshi and Rosenzweig (2009), for example, show that castes serve as insurance networks in rural India. While this an example of a role inherited form the past, castes have also evolved to take advantage of new opportunities. This is particularly true in the political sphere, where as previously mentioned, some caste groups act as lobbies to defend their groups’ interests.

1.2 How are castes related to human capital?

The previous section highlighted the importance of caste as an institution governing social life in contemporary India. In parallel, caste is also a strong determinant of socio-economic outcomes and in particular of educational attainment. Even if some convergence in educational attainment across caste groups has occurred (Kijima, 2006; Desai and Kulkarni, 2008), there is still a clear relation between the hierarchical position of a given caste group and its education level. Lanjouw and Stern (1998), who have been studying the village of Palanpur in Uttar Pradesh over five decades, note that in this village caste literacy rate is correlated to the caste status and even that “statistical analysis suggests that caste has an influence of its own [on the education level], independently of per capita income (and even after controlling for parental education)”. This pattern is confirmed at the national level. Since 1931, there has been no official Indian survey where people were asked for their caste group, so it is impossible to exactly match education level and caste. However, data provide separate information for “scheduled castes” (SC), “scheduled tribes” (ST) and “others”. And the gap between SC/ST and the others is striking: according to Kijima (2006), in 1999, 41.1% of the ST

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6Except in the Census of 2011, but data are not yet available.
7Data are from the 55th round of the national sample survey. North-eastern States are not included.
and 32.9% of the SC households had no literate member, against “only” 18.1% of
the other groups. Similarly, 13.6% of the other households had a member with a
university level or above, against only 4.2% of the ST households and 5.3% of the
SC households.

This situation has been inherited from centuries of discrimination against low
castes, who had no access to education. But even now that low castes have equal
access to education,\textsuperscript{8} they do not have equal treatment. The first source of in-
equality is through the kind of school that low castes can access. Because private
schools tend to be of better quality than public schools in India, in some villages
a situation has emerged where low castes students go to public schools and high
castes students go to private schools. And even when low castes students at-
tend the same schools as high caste students, they still suffer from differential
treatments: for example dalits have to sit on the floor when their counterparts
seat on benches. Discrimination does not only come from other students. It is
also reported that teachers have negative attitudes towards low castes students,
going from indifference to physical punishments [PROBE report, 1999]. Hanna
and Linden (2012) also find that teachers give lower grades to low castes than
to high castes for similar answers in exams. Moreover, these phenomenon are
not restricted to rural areas. The PROBE report quotes a teacher in Delhi: “What
is the point of teaching scheduled-caste children? Let them learn how to beat
drums, that’s good enough.”. Low castes students also suffer from discrimination
at higher level of education. Harassment against dalits by other students has
been reported in elite universities, and in several cases it even conducted them to
commit suicide.\textsuperscript{9}

This strong correlation between caste status and educational attainment is
reinforced by the lack of opportunities that low castes face. Indeed, low castes
have a lower return to education (Kijima, 2006) and have therefore less incentives
to invest in education.

There are several reasons for these lower returns to education. First, it is
related to the division of labor across castes, and to the fact that low castes were
historically restricted to low-skilled jobs. Even though things are changing, most
low castes continue to work in the area where members from their jati work, where
returns to education are low. Studying the response of low castes to a positive

\textsuperscript{8}In 2011 school enrollment rate in India was 100%. The numbers can be misleading, because
of the double counting of children who are enrolled in public and private schools, but it really
denotes an almost universal access to education.

\textsuperscript{9}The documentary film “Death of Merit”? describes this situation. It is available online at
http://thedethofmeritinindia.wordpress.com/.
shock to returns to education in Mumbai, Munshi and Rosenzweig (2006) find that
the answer is stronger for low caste girls than low caste boys, because boys are
expected to work in the subcaste traditional occupation, which does not require
high education levels. On the contrary girls are more responsive in terms of
educational investment, because they were historically kept away from the labor
market and are therefore not tied up to the traditional occupation.

Second, getting employment in the formal sector requires connections. Lan-
jouw and Stern (1998), looking at the outside jobs secured by the inhabitants of
Palanpur, find that all the members from a subcaste having a job outside of the vil-
lage tend to have the same job or work in the same company. Their interpretation
of this pattern is that it “reflects the nature of the job search process in this seg-
ment of the labour market, which operates through ‘contacts’ rather than through
‘impersonal’ search by prospective employees (or employers). Those who have
already secured a job outside the village are usually in a privileged position to
help their friends, relatives, or fellow caste members to take advantage of possible
vacancies in their own place of employment; and employers themselves often use
their existing employees as recruiting agents”. Therefore, it is more complicated
for low castes to secure white-collar jobs, because their network outside of the
village is less developed than the one of higher castes. And this is not only true
for private sector jobs. Although there are quotas for low castes for jobs in the
public sector, connections are also needed because the hiring process is highly
discretionary. This point is further explained in chapter 4.

Finally, it is possible that there is discrimination against low castes in the
recruitment process. Indeed, high castes are overrepresented in the private sector,
in the ownership of firms as well as in the workforce (Iyer et al., 2013).

1.3 Improving low castes’ human capital

The two previous subsections give a very negative overview of the situation.
Low castes seem to be stuck in a poverty trap, with low education levels and
little opportunities. However, according to the literature, the educational gap
between low castes and high castes seems to be slowly shrinking (Desai and
Kulkarni, 2008). Moreover, intergenerational mobility of SC/ST in terms of educa-
tion and income has reached the level of non SC/ST during the 1983-2008 period
(Hnatkovska et al., 2013). These facts underline that things can and are actually
changing. This section focuses on two different possibilities for low castes to im-
prove their economic position: the use of caste networks’ strength and affirmative
action programs.
The caste system has been described as an institution which prevents mobility. However, there are cases where the strong links that connect castes members to each other have been used by castes groups to move into new occupations. Although most of the success stories are of high castes (Damodaran, 2008), Munshi (2011) describes the case of a low caste of agricultural laborers, the Kathiawaris, who succeeded to enter the diamond industry business in Mumbay. The rule of intra-caste marriage was notably used as a tool to reduce commitment problems.

However, the principal instruments available to low castes to improve their economic status are affirmative action programs. Affirmative action in India has a long history: as early as 1882 the British created special schools for Untouchables (Jaffrelot, 2011). But it was after Independence that reservation policies were implemented on a large scale. Although there was no consensus between Independence leaders on how to improve low castes status, “reservations” in favor of the Untouchables, now called the “Scheduled Castes” (SC) were written in the Constitution. The SC, as well as the ethnic minorities (called Scheduled Tribes, ST) were provided with respectively 15% and 7.5% quotas in the administration, in public universities and in elections.

This reservation system was latter extended to the Shudras. The extension of the system of quotas to this category of population, now called the “Other Backward Classes” (hereafter OBC) was however very gradual and a large freedom was left to States governments to legislate on this matter. The reason for this flexibility on reservations for OBC was due to the controversial aspect of this policy. The OBC constitute almost 50% of the Indian population. Therefore, extending the quotas to this whole population is not anecdotal and lowers the number of remaining seats for the other castes. The OBC population is also very heterogeneous, contrary to the SC/ST who are almost without any exception very deprived. Given that they suffer less from discrimination, prior to reservations, some OBC had the opportunity to improve their economic status and cannot be considered anymore as disadvantaged. Moreover, among the OBC, some jatis as a whole enjoy locally very influential positions due to their landholding position.

This situation made it complicated for the Central
government to come up

10The main opposition was between Gandhi and Ambedkar, who had conflicting ideas about how to improve Untouchables status.
11This estimation comes from the Mandal Commission, which was established in 1979 with the mission of making a report on the status of the OBC. However, this number is controversial, because it has been calculated with figures from the 1931 census, the last census with details by jatis.
12The word “Central” is used to refer to what is defined at the federal level, and the word “State” to what is defined at the State level.
with a consensus on reservations for OBC. Therefore, the question was left to the States, which independently created positive discrimination for OBC. The first States to implement reservations on the same basis as those for SC/ST were the four southern States (Kerala, Karnataka, Andhra Pradesh and Tamil Nadu) (Galanter, 1978) and the last were the States of the Hindu Belt (Rajasthan, Haryana, Uttar Pradesh, Madhya Pradesh). The Central Government finally caught up the movement by establishing in 1993 reservations for OBC in the Central administration and since 2008 27% of the seats in Central Universities are reserved for OBC.

Therefore, there is now 49.5% of the seats in higher education institutions reserved for low castes in India. This goes along with scholarships, free meals, etc. at lower levels of education. Whether it has been effective so far is however a matter of debate. For example Cassan (2011), who exploits the States borders’ changes to evaluate the impact of affirmative action on the education level of scheduled castes, finds no impact. On the contrary, Bertrand et al. (2010) who look at the economic status of low castes who got into higher educational institutions thanks to quotas find that low castes who benefited from affirmative action are richer than those who did not.

2. How do others matter?

In the previous section, I have described how human capital in India is closely related to the institution in which social capital is created, the caste, and what are the mechanisms which are designed to break this historical situation where high castes have a lot of human capital and low castes have very little. In this section, I want to further explore the relationship between social capital and human capital, by broadening 1) the geographical focus, and 2) the question. More precisely, this section goes back to the question asked at the beginning of this introduction: how do others matter in relation to human capital? The literature in relation to this question is explored looking at two different perspectives, which are those that I consider in this dissertation: how does the human capital of others influence productivity? and how do others have an impact on human capital formation?

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13In India, there are two kind of universities: the “Central Universities”, which depend on the Central government of India, and the “State Universities” which are administered by State governments.
2.1 How does the human capital of others influence productivity?

The human capital of others has an impact on individual or aggregate productivity through three channels. The first channel relates to knowledge spillovers. Individuals learn from their co-workers or neighbors who have more human capital, which in turns increases their individual productivity. The second and third channels are composition effects of human capital. The second channel depends on the complementarity between different levels of human capital (Kremer, 1993). If tasks and different levels of education are complementary in the production function, then the way the education is distributed in firms or in an economy as a whole has an impact on aggregate productivity. The same is true for the third channel. If returns to human capital are not linear in the level of human capital (Elbers and Gunning, 2004), which means that the marginal returns of human capital is not the same for low and high levels of education, then again, the way the education is distributed in an economy has an impact on aggregate productivity.

The first channel has therefore an impact on individual and aggregate productivity, while the impact of the second and third channels is only visible at the aggregate level. The empirical estimation of the impact of the human capital of others in the economy therefore follows two paths: one kind of literature estimates the impact of the composition of human capital in the economy on growth or productivity at the aggregate level, in which case there is no distinction between the three channels. The second kind of literature looks directly at the impact of co-workers or neighbors on individual productivity and is therefore only interested in estimating the impact of the first channel, knowledge spillovers.

The literature at the aggregate level focuses on the impact of inequality of education on productivity and growth. It is a fairly recent literature, which finds contradictory results. Londono and Birdsall (1997); Lopez et al. (1998), Castelló and Domenech (2002) and Castelló-Climent (2010b) find a negative impact of education inequality on income growth or income per capita. On the contrary, the impact is positive for Schipper and Hoogeveen (2005), Park (2006) and Rodríguez-Pose and Tsélios (2009). The reasons for this discrepancy in the results will be explored in chapter 1. However, what can already be said from this list of results is that further research on this issue is required in order to understand what is the impact of the distribution of education on the economy of a country.

The literature specifically considering education spillovers is much more de-
INTRODUCTION

Developed. Here I only focus on the papers that I consider as the most important, because of their identification strategy or the context in which they study education spillovers.

As mentioned before, education spillovers can be observed at the aggregate level. This is what Acemoglu and Angrist (1999), Ciccone and Peri (2006) and Moretti (2004a) do, by comparing wages of workers in cities with more or less human capital. Acemoglu and Angrist (1999) do not find any impact, but Ciccone and Peri (2006) and Moretti (2004a) find that a higher share of college graduates in a city increases workers productivity.

A positive result is also found when education spillovers are studied at the plant level. Martins and Jin (2010), who use panel data on firms in Portugal, and Moretti (2004c), who looks at firms in the US, find important knowledge spillovers. The evidence is not as clear in the literature looking at education spillovers in a non-industrial context. Three papers study the impact of neighbors’ human capital on agricultural productivity. Appleton and Balihuta (1996) and Weir and Knight (2007) find that the surrounding human capital matters for productivity. On the contrary, Asadullah and Rahman (2009) find no impact of neighbors’ education on agricultural productivity. Again, these results, and the reasons why there is no consensus will be discussed in more details in chapter 2.

Among the papers previously quoted, none on them specifically focuses on India. Most papers at the aggregate level are concerned with the United States or developed countries in general. The exception is Lopez et al. (1998) who use panel data on 12 developing countries between 1970 and 1994. At the microeconomic level, the literature looking at education spillovers in plants also only uses data from developed countries. However, the literature studying agricultural productivity focuses on developing countries: Appleton and Balihuta (1996) and Weir and Knight (2007) look at education spillovers in farm productivity in Africa, and the geographical focus of Asadullah and Rahman (2009) is Bangladesh. The only related literature which is specifically about India is the one studying peer effects in the adoption of new technologies in agriculture. India is indeed a country where the Green Revolution rapidly expanded and succeeded. Worth mentioning are the papers by Foster and Rosenzweig (1995), who find important learning effects in the adoption of high yielding grains in India during the Green Revolution, and by Munshi (2004) who finds that learning from neighbors is weaker when the productivity of the new technology depends on unobservable individ-

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14 A good overview of the research on this issue, as well as on the impact of the surrounding human capital on other issues is provided in Moretti (2004b).
The fact that others influence productivity, at the individual or aggregate level, is one aspect of the interaction between human capital and social capital. However, maybe even more important is how social capital interacts with human capital \textit{ex-ante}. In other words, how does social capital influence human capital formation? The next section reviews the literature dealing with this question.

### 2.2 How do others influence human capital formation?

The question of how others influence human capital formation was actually the first question asked when the concept of social capital was created. The seminal paper on social capital of the sociologist Coleman (1988) is indeed entitled “Social capital in the creation of human capital”. This paper is interested in how social capital in the family and in the community influences the creation of children’s human capital and underlines important correlations between measures of social capital and dropout rates. But more importantly, this paper introduces the concept of social capital and opens the way to further research on this issue. Since this first paper, research on the topic has exploded, although most of the literature only considers social capital in a very reduced meaning: the core of the literature concentrates on the impact of peers’ educational performance on children’s performance, where performance is measured with test scores or dropout. Sacerdote (2011), who provides a review of this literature, underlines that there is a consensus on the existence of peer effects in educational outcomes.

Maybe more relevant to the topic on hand, is the literature which studies neighborhood effects on children’s school achievement. In this literature there is no consensus on the fact that neighbors’ characteristics have an impact on children’s performance. For example, Goux and Maurin (2007) find that the proportion of uneducated families in the neighbors has a positive impact on the probability of repeating a year. On the contrary, Gibbons et al. (2013) find no impact of changes in the neighborhood composition on test scores. According to Patacchini and Zenou (2011), this variety of results can be explained by the fact that the impact of the neighborhood is complex, and may not be linear. This is indeed what they find when they study the impact of the quality of the neighborhood on children’s education. They find that neighborhood quality and parents’ involvement are complementary and neighborhood quality matters more for lower educated parents.

Taking a broader perspective, peers and neighbors seem to also have an impact on education related choices. De Giorgi et al. (2009), studying the choice of major
of students at the University of Bocconi, find that they are highly influenced by the choice of their peers, leading to a mismatch between skills and qualifications in the labor market. Similarly, Marmaros and Sacerdote (2002) find that the probability that students take high paying jobs increases with the mean parental income of their dormmates during their first years as freshman. However, they are not able to differentiate if this is because students were influenced by their peers, or if they get concrete help from their peers to get a high paid job. But again, there seems to be no consensus on the question: Arcidiacono and Nicholson (2005) find that there are little peer effects in the choice of speciality for American medical school students.

There is also an extensive literature on how others influence opportunities, through their impact on employment outcomes. As underlined earlier, opportunities have an indirect effect on human capital formation, because people invest in education according to their expected returns. It has been shown that people notably use their network to get information about jobs (for empirical evidence, see for example Corcoran et al. (1980), Topa (2001) or Wahba and Zenou (2005)). Social networks are also useful because they play the role of referral (Topa, 2011). Consequently, networks decrease unemployment duration (Cingano and Rosolia, 2012).

How does this literature relate to India? Again, none of the papers previously mentioned is specifically concerned with India, and very few are about developing countries. However, what is interesting to see is that a growing literature considers that the ethnic group is where social capital is created. Little is still known about the role of ethnic networks in the direct creation of human capital, because ethnicity is usually taken into account by including dummies. But the literature begins to understand the role played by ethnic networks in jobs and career opportunities (see for example Munshi, 2003; Edin et al., 2003; Patacchini and Zenou, 2012). One interesting paper which directly makes the link between job opportunities and human capital investment is the one by Munshi and Rosenzweig (2006), mentioned above. They show that ethnic networks may not have always a positive impact. In particular here, they find that caste networks are possibly inefficient because there was little reaction in terms of educational investments for low castes to an increase in returns to education.
3 Outline of the thesis

This dissertation fits into the literature just mentioned by studying how productivity at the aggregate level and at the individual level is impacted by the human capital of other people in the economy, and how human capital creation is driven by social capital, directly or indirectly through available opportunities. The structure broadly follows the outline chosen to expose the literature. Chapter 1 and 2 look at the link between productivity and others’ human capital, and Chapter 3 and 4 study the impact of caste on application to affirmative programs, which make the access to universities (chapter 3) and to jobs in the public sector (chapter 4) easier for low castes. Although the order of the four chapters can appear counterintuitive at first sight (one could expect to begin with the creation of human capital and to end with the impact of human capital), this organizational choice is actually driven by how “others” are defined in the four chapters. The direction of this dissertation goes towards a narrowing of the definition of “others”. In chapter 1, “others” is defined broadly and refers to all other workers in the economy. In the subsequent chapters, “others” refers to individuals’ group, where the group under study is the individual’s varna in chapter 2 and the individual’s jati in chapter 3 and 4. Similarly, the perspective is narrowing: chapter one is a macroeconomic work on Indian States, whereas chapter 2 to 4 have a microeconomic focus.

The objective of chapter 1 is to provide a macroeconomic perspective on how the human capital of others matter for aggregate productivity. As underlined in the literature review, when considering this issue researchers have focused on the impact of the inequality of human capital. This is also the approach that is taken here. More precisely, this chapter empirically analyses the relation between the distribution of education and income per capita of Indian States with six rounds of households’ surveys, the NSS data, between 1983 and 2009-2010. Using two different measures of the distribution of education, a Gini of education and a Theil index, and dealing with the high correlation between the mean education level and its distribution by separating the “level effect” from the “composition effect” in the Gini coefficient, this chapter provides evidence that there is a negative relation between the equality of education and income per capita. This relation is however not linear and depends on the level of development: the relation is negative for richer States, but poorer States have an income per capita positively correlated (but not always significant) to the equality of education. As previously mentioned in section 2.1, the channels which may explain this impact are threefold: there may be education spillovers, the returns to education may be non-linear, and/or there may be complementarity between workers education level. In a second
part, I consider these three channels successively. Data are limited - they do not cover the whole period- so too much emphasis should not be put on the results. But I find that all the three channels seem to play a role in explaining the relation.

**Chapter 2** is a direct extension of chapter 1. It also explores how the human capital of others matter for productivity, but this question is now studied taking a microeconomic perspective. The focus is also more restrictive: in this chapter, the area of study is *rural* India, the reason being that the productivity which is taken into consideration is *agricultural* productivity. The objective is to analyze if there are education spillovers in rural India, by evaluating the impact of neighbors’ education on farm productivity. To overcome the identification problem related to the endogeneity of network formation, I exploit the fact that social interactions mainly occur along caste lines in rural India. Defining neighbors as members from the same caste also permits to rule out that the measured impact of members from the same caste is a spurious correlation due to unobservable characteristics.\(^{15}\)

Using a household survey representative of rural India, The ARIS-REDS data, the results show that education spillovers do exist: one additional year in the mean level of education of members from the same caste increases households’ farm productivity by 5%. The impact of neighbors’ education decreases with households’ level of education, showing that neighbors and households’ head education are substitutes. I also find that education spillovers vary across crops. They are lower for rice than for wheat. This may be due to the fact that learning from others in rice is more complicated, because rice productivity depends a lot on fields’ characteristics.

After having shown that the human capital of others has an impact on productivity, the rest of the dissertation is concerned with the broad question of how others matter in the creation of human capital. In **chapter 3**, I study the determinants of households’ application for affirmative action programs in education in India, with a focus on the role of social stigma, where social stigma is defined as the disutility arising from participation in a program (Moffitt, 1983). Affirmative action enables low castes to have an easier access to higher education through quotas in public institutions. To measure stigma, I look at the Other Backward Classes (OBC) and I analyze the impact of the status of households’ subcaste on their probability of applying for reservations. If there is stigma, we expect households from castes with a higher social status to have a lower probability of applying for reservations. The identification strategy is based on the fact that the

\(^{15}\)This is true under certain hypotheses which are discussed in more details in the chapter. This strategy is the one used in Munshi and Myaux (2006).
INTRODUCTION

OBC group is composed of subcastes which are very different in terms of social status. The status of a subcaste group in rural India is locally determined and is strongly related to the proportion of land owned by this subcaste in the village. I use this exogenous and historical variation of status to identify the stigma effect.

I find that the probability of applying decreases with the social status of the caste group from which the household is from. This result can be interpreted as a stigma effect which leads households from locally high ranked groups to apply less for reservations in higher education.

Finally, chapter 4 is concerned with affirmative action programs in the public sector, which provide reserved jobs for low castes in the administration. These programs, by changing the access of low castes to jobs that were in the past preempted by high castes, also changed low castes expected returns to human capital. However, the goal here is not to directly assess if those quotas had the effect of increasing low castes human capital. I consider reserved jobs under a slightly different, but related, angle: I am interested in the concrete access to those reserved jobs. Indeed, for the actual expected returns to education to be higher, low castes need to be concretely able to get the jobs. However, while any low caste can apply, the recruitment is highly discretionary and the recruiters can hire who they want (Chandra, 2004). Therefore, intermediaries and networks play an important role in providing access to those jobs. In this chapter I am looking at the impact of caste networks in getting access to reservations in the public sector. More precisely, I exploit political reservations for low castes to study the impact of having an elected local leader on low caste households’ applications for reserved jobs in the public sector. Using data from 37 villages from three South Indian States from the ARIS-REDS survey, I find that households apply significantly more for reserved jobs when the council president is from their caste group. This seems to be due to a “patronage effect”, where the council president uses his connections to help his caste-fellows to get a reserved job. These results show that access to reserved jobs is uneven across caste groups, because members from well connected castes have a facilitated access to higher levels of the administration. The expected returns and consequently investments in human capital are therefore likely to be different across caste groups, depending on their characteristics.

Overall, this thesis contributes to the growing literature which moves the focus from the private individual to the group, by looking at the interactions happening between human capital and castes. It provides some empirical support to the idea that human capital is related in several dimensions to social capital in general and to castes in particular. It therefore strengthens the idea that caste is still
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an unavoidable institution in India. Additionally it sheds some light into two important questions which are currently heavily debated in India. Chapter 1 and 2 contribute to the debates on the growing role of private education in India. These chapters, by showing that there are external returns to education, emphasize the need for a coherent education policy which does not only rely on private schools. Chapter 3 and 4, which find that application to quotas for low castes in higher education and in jobs in the public sector depends on several caste characteristics and notably on caste power, call for a large scale evaluation of the efficiency of affirmative action programs based on caste membership criteria.
Chapter 1

Distribution of education and income per capita: empirical evidence from Indian States
1 Introduction

In 2009-2010, the working-age population of Karnataka and Assam, two Indian States, had on average the same level of education (respectively 6.2 and 6.1 years of education). However, the pattern of distribution of their human capital was very different. Whereas in Karnataka 31% of the population was illiterate but 10% had a tertiary education, in Assam, only 18% was illiterate and 4% had a tertiary education. What are the consequences of different distributions of human capital? Which education policy favors economic development? The necessity of increasing human capital is not anymore a matter of debate, but the way it should be done is still an open research question.

Of course, the answer to what should be done depends on what outcome we have in mind. Development can mean higher growth and higher income per capita for some, and equality of opportunities for others. The answer will strongly differ depending on what one is thinking about. For example Castelló-Climent (2008) finds that a more equal distribution of human capital is good for democracy, whereas Park (2006) finds that a greater inequality of education favors income growth. The goal of this paper is not to look at the impact of the distribution of education on all the facets of development. In this paper, I only discuss the relation between distribution of human capital and income per capita, using data from Indian States between 1983 and 2009-2010.

The direction of the relation between distribution of education and income per capita is a priori not clear. The theoretical literature underlines three channels through which the distribution of education is related to income per capita and the three channels have contradictory impacts.

The first channel is that the return to education may not be linear in the level of education (Elbers and Gunning, 2004). If this is the case, the impact of the distribution of education on income per capita depends on the returns to education in terms of productivity. If the returns’ curve is concave in education, the marginal productivity of workers with high level of education is lower than the marginal productivity of workers with low level of education. Therefore, a more equal repartition of education has a positive impact on income. On the contrary, if the returns’ curve is convex, inequality of education has a positive impact on income. Recent empirical evidence has underlined that the curve of returns to education in terms of wages is convex in India (Colclough et al., 2010).1

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1Due to data availability, these estimates are only based on wages estimations. Since a large part of individuals are self-employed, the return to education could be different when taking into account this population.
If wages are equal to the marginal productivity of workers, then in India a more equal distribution of education is expected to have a negative impact on income per capita.

The distribution of education also matters if there are externalities of education, through learning spillovers. Learning spillovers are usually assumed to go from high educated workers to low educated workers (Moretti, 2004b), in which case a less equally distributed human capital should have a positive impact on income per capita.

Finally, if workers with different education levels are complementary in the production process, then the distribution of education also matters. Kremer (1993) underlines that when tasks are also complementary, the optimal matching of workers is when workers of similar skills work together. This matching is achieved in labor markets without frictions. However, in labor markets which are not perfect, the distribution of education matters for income per capita, because a more unequal distribution of human capital lowers the probability that workers of similar skills can be matched together. Therefore, according to this channel, a more equal distribution of education should increase income per capita.

To summarize, the two first theoretical channels predict a negative relationship between equality of education and income per capita in India, whereas the last channel predicts a positive relationship. The overall relation between education distribution and income per capita is therefore an empirical question.

However, empirically there is still no consensus on the direction of the relation. Londono and Birdsall (1997), Lopez et al. (1998), Castelló and Domenech (2002) and Castelló-Climent (2010b) find a negative correlation between education inequality and income growth or income per capita. On the contrary, Schipper and Hoogeveen (2005), Park (2006) and Rodríguez-Pose and Tselios (2009) find a positive relation.

It is hard to point out what could drive this variety of results, because the comparison is difficult due to the diversity in the geographical coverage of those studies. For example, Lopez et al. (1998) focus on a panel of developing countries, Castelló and Domenech (2002) mix developing and developed countries and Rodríguez-Pose and Tselios (2009) only have developed countries in their sample.

Several hypotheses can still be formulated. The absence of consensus could be explained by methodological issues. Except for Schipper and Hoogeveen (2005), who study the impact of education inequality in rural Uganda, the identification of the impact in this literature only relies on cross-sections or large panels of countries. The heterogeneity that exists between these different countries is obviously
hard to be taken into account and could drive the results that the authors get.

This literature also ignores that the distribution of education is highly correlated with the mean level of education (Thomas et al., 2001). Multicollinearity can make it difficult to uncover the partial effect of each variable (Wooldridge, 2003), and can also generate spurious estimates when the two highly correlated variables have a small explanatory power (Chatelain and Ralf, 2012).

Finally, the same pattern of results could be obtained if the relation between human capital distribution and income per capita is not linear and depends on the level of development as underlined by Castelló-Climent (2010b). If this is the case, the effect may vary a lot depending on the chosen sample of countries.

This paper therefore aims at bringing complementary evidence on the relationship between education distribution and income per capita, while improving previous literature on a methodological point of view. To avoid the great heterogeneity that exists across countries, I focus on a single country, India and use panel data on Indian States over 25 years. I deal with the high correlation between the mean education level and its distribution by using an equality index of education built following a methodology proposed by Berthélemy (2006). I find that there is a negative relation between the equality of human capital and the income per capita of Indian States. The relation differs depending on the level of development. The relation is negative in richer states, but positive (although not always significant) in poorer States. This result gives credit to the hypothesis that non-linearities may drive the diversity of results found in the literature.

The second objective of this paper is to explore the channels which drive the relation. While the literature has explored some channels that lead to an impact of education distribution on growth (Castelló-Climent, 2010a), there is no paper looking at the relation between education inequality and aggregate income or income per capita. Given the small amount of data available, one has to be careful on the conclusions. Nonetheless, the three channels previously underlined seem to play an important role in explaining the relation between distribution of education and income per capita.

The methodological improvements and the non-linearity results are the main contribution of this paper to the literature. However, this preliminary exploration of the channels is also informative, and nothing in that direction had been made so far.

The rest of the chapter is organized as follows. Section 2 explains the distri-

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2This point will be further explained in section 2.
bution variables used and in particular the construction of the education equality index. Section 3 and 4 present the data used and the empirical methodology. The results are shown in section 5 and section 6 empirically explores the theoretical channels. Section 7 concludes.

2 Measures of the distribution of education

In the literature on the distribution of education, two different kinds of measures are used. The first category includes sample moments of the distribution, such as the variance of schooling. The advantage of the variance is that it is simple to compute. However, it does not have the properties that are required from a good measure of inequality. In particular, it only measures the inequality in absolute terms (it is not bounded) (Thomas et al., 2001) and it is not scale invariant. The second type copes with these limitations by notably measuring the inequality in relative terms. The most widely used are the Gini of human capital and the Theil Index. I focus on these two indicators in this paper.

2.1 The Gini coefficient of human capital

The Gini coefficient of human capital can be calculated as follows (Castelló and Domenech, 2002):

\[ G_H = \frac{1}{2H} \sum_{i=0}^{n} \sum_{j=0}^{n} |\hat{x}_i - \hat{x}_j| n_i n_j \] (1.1)

Where \( G_H \) is the Gini of human capital, \( \bar{H} \) is the mean level of education, \( i \) and \( j \) are the levels of education, \( \hat{x}_i \) and \( \hat{x}_j \) are the cumulated years of education for levels \( i \) and \( j \) of education and \( n_i \) and \( n_j \) are the share of people with a given level of education.

Like the classical Gini used to estimate the inequality of income, the Gini of human capital can be represented graphically with a Lorenz curve as in figure 1.1. The different levels of education are on the vertical axis and the cumulative proportion of people with a given level of education is on the horizontal axis. The Gini of human capital is two times the area between the Lorenz curve and the diagonal which represents perfect equality.

One issue with this index, as documented by Thomas et al. (2001), is that it is highly correlated with the mean level of education, and this correlation is higher in developing countries. The reason is twofold. First, the distribution of human capital is bounded: one cannot have more than a PhD level, that is to say
more than approximately 20 years of education in most countries. Consequently, when the mean level of education increases, it cannot be the level of the most educated people which increases, but the level of less educated people, so the Gini of education automatically decreases. Second, the Lorenz curve is truncated along the horizontal axis (Thomas et al., 2001). As there is a large proportion of individuals are in developing countries, a low mean level of education is associated with a high value of the Gini coefficient (see figure 1.1).

Figure 1.2 shows the relation between the Gini of human capital and the mean level of education in Indian States with six rounds of data between 1983 and 2009-2010. There is a strong negative correlation between these two variables, which seems to be even stronger for low levels of education.

2.2 Decomposing the Gini coefficient into its level and composition effect

This very high correlation between the mean level of education and its distribution complicates the estimation of the impact of the distribution of human capital. First, it creates econometric issues. Multicollinearity often provides too large standard errors (Wooldridge, 2003), or generate spurious estimates when the two highly correlated variables have a small explanatory power (Chatelain and Ralf, 2012). Second, it makes it difficult to understand if the measured impact of the distribution of human capital is actually a mean effect or a real distribution effect.
One solution is to disentangle in the Gini coefficient the level effect of education from the concentration effect. For this, I follow the theoretical work of Berthélemy (2006). Within a simple framework where there are only four different levels of education (no education, primary education, secondary education, higher education) and where each level has the same number of years, Berthélemy (2006) shows that the Gini of education can be written as a function of the mean level of education and a function \( \Gamma \) which depends on the structure of schooling. Following his notations:

\[
G_H = 1 - H \Gamma(\theta, \tau) \tag{1.2}
\]

With

\[
\Gamma(\theta, \tau) = 1 - 2\left(\frac{\theta + \tau + \theta \tau}{(1 + \theta + \tau)^2}\right) \tag{1.3}
\]

Where \( G_H \) is the Gini of human capital, \( H \) is the aggregate level of human capital, \( \theta \) and \( \tau \) are respectively the ratio between the rate of secondary schooling and primary schooling and the ratio between the rate of tertiary schooling and primary schooling. For not too large values of \( \theta \) and \( \tau \) (which is the case in my data), \( \Gamma \) decreases with \( \theta \) and \( \tau \). \( \Gamma \) is consequently a measure of the equality of a schooling system and can be computed following equation (2): \( \ln \Gamma = \ln(1-G_H) - \ln H \).
Figure 1.3 shows the relation between the “education equality index” (Γ) and the mean level of education in my data.\(^3\) As we can see, the correction is not perfect: there is still some correlation between the mean level of education and the corrected Gini. One explanation to this persistent correlation, suggested by Berthélemy (2006), is that the ratios of relative schooling \(θ\) and \(τ\), on which the education equality index depends, are related to aggregate human capital. The supply of education depends on the presence of skilled teachers in an economy, which itself depends on the aggregate human capital. But primary education depends less on the presence of skilled teacher than secondary education, which itself depends less on skilled teachers than tertiary education. This would explain why \(θ\) and \(τ\), and therefore the equality index of human capital, would be correlated to the aggregate human capital. However, the correlation is much lower and this specification of the Gini coefficient reduces multicollinearity issues in the estimation.

\(^3\)To get a more precise definition of the mean education and of the equality indicator as well as to minimize measurement errors in the empirical specification, I use eight levels of education described in table A1.1 in the appendix. So this specification does not follow exactly Berthélemy (2006)’s theoretical model.
2.3 The Theil index of Human Capital

To make sure that the results are not driven by the use of the education equality index, I also use another inequality measure, the Theil index. The Theil index is widely used and has the advantage of being more sensitive to changes at the top of the distribution. The formula of the Theil index is as follows:

\[ T_H = \frac{1}{N} \sum_{i=1}^{N} \frac{H_i}{H} \ln \left( \frac{H_i}{H} \right) \]  

(1.4)

where \( H \) is the mean education, \( H_i \) is the education level of individual \( i \) and \( N \) is the number of individuals in a given State.

3 Data

To estimate the relation between the distribution of education and income per capita, two types of data are used. For the dependent variable, income per capita, I use data from the Reserve Bank of India. It provides the net State domestic products per capita. For several States, the data were not available for the whole period (1984 to 2010-2011). Furthermore, three States have been split during the period. So out of the current 35 States and Union Territories the relation between education equality and income per capita can only be estimated for 29 States and 162 observations.

The other data come from six rounds of household surveys conducted by the National Sample Survey Organization in 1983, 1987-88, 1993-94, 1999-2000 and 2009-10. These surveys, the NSS, are conducted approximately every five years and provide rich information on households’ consumption, employment and educational attainment.

To build the education equality index, I need to convert educational attainment into years of education. For this, I use the same classification as Kingdon and Theopold (2008). The conversion table is given in table A1.1 in the appendix. The mean level of education and the equality indicator are then computed using only the working-age population (more than 15 years old).

\footnote{It is therefore less correlated to the mean than the Gini, because it puts more weights to changes really related to the distribution.}

\footnote{There are no estimates at all for Dadra and Nagar Haveli, Daman and Diu and Lakshadweep; for Mizoram, there are no consistent estimates for 1984, 1988-89 and 1994-95; for Sikkim, Goa, Nagaland and Chandigarh for 1984 and 1988-89 and for Arunachal Pradesh there is no estimates for 1984. The States with at least three observations are kept because it is the minimum required to do a System GMM.}

\footnote{Chhatisgarh has been created out of Madhya Pradesh, Jharkhand out of Bihar and Uttarkhand out of Uttar Pradesh. I treat these States as they were in 1983.}

3. DATA
The other variables are also computed with the NSS. I notably use the consumption data to proxy for income inequality, as it is commonly done for countries where income data are not very reliable.

4 Empirical specification

The econometric specification to estimate the relation between the distribution of education and income per capita is as follows:

$$\ln Y_{it} = \beta_1 \ln H_{it} + \beta_2 X_{it} + \beta_3 \text{DIST}_H_{it} + \beta_4 GINIcons_{it} + \beta_5 \text{FRAC}_{it} + \gamma_t + a_i + u_{it}$$

where $Y_{it}$ is the income per capita of State $i$ at time $t$, $H_{it}$ is the mean level of education of the State working-age population, and $X_{it}$ is a set of control variables at the State level. $\text{DIST}_H_{it}$ is the education equality index or the Theil index depending on the specification.

As the distribution of human capital is related to the distribution of incomes, which may have an independent impact on income per capita, I also control for the income distribution in the State, which is proxied by a consumption Gini index, $GINIcons_{it}$. In the same manner, ethnic diversity has been reported to be correlated to income per capita, for reasons not related to the distribution of education (Easterly and Levine, 1997). In India, individuals’ human capital is strongly correlated to one’s caste group, so the education equality index may capture some effects due to caste diversity. To take that into account I add a caste fractionalization index which measures caste diversity in the State. For the fractionalization index, I use the following formula: $\text{FRAC}_{it} = 1 - \sum_{g=1}^{N} s_{git}^2$ where $s_{git}$ is the share of group $g$ in State $i$ at time $t$. This index represents the probability that two randomly selected individuals belong to different ethnic groups. The consumption Gini and the fractionalization index therefore control for the other distributional effects that the equality index would have captured otherwise. I also control for shocks common to all States by adding time dummies represented by $\gamma_t$.

There are concerns about endogeneity. The fact that the variable of interest, the distribution of education is calculated on more than 15 years old individuals rules out any reverse causality problem. But the distribution of education may be

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7 The proportion of workers in agriculture and in the manufacturing sector, electricity consumption per capita and State expenditures per capita.

8 Data from the surveys do not give as detailed group definitions as the data used by Banerjee and Somanathan (2007) Consequently, the fractionalization index used here is built on only 3 groups: scheduled castes, scheduled tribes and others.
correlated to factors also influencing income per capita. I control for time-invariant unobservables by adding State dummies \( a_i \) and standard errors are clustered at the State level. To also deal with endogeneity issues concerning the other control variables, all right hand side variables are lagged nine months\(^9\) and robustness checks are conducted with an alternative panel data method, the Blundell and Bond (1998) system GMM. The identification is further questioned in section 5.2.

5 Results

5.1 Estimation with State fixed effects

The results of the estimation in fixed effects with the education equality index are shown in table 1.1.

<table>
<thead>
<tr>
<th>Table 1.1: Variable of interest: Equality of education index estimated with FE</th>
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<tbody>
<tr>
<td>Dependent variable: Net State domestic product per capita</td>
</tr>
<tr>
<td>(1) (2) (3) (4) (5) (6) (7)</td>
</tr>
<tr>
<td>Mean Educ (log) -0.532* -0.552** -0.575** -0.604** -0.644*** -0.500* -0.686**</td>
</tr>
<tr>
<td>(0.265) (0.256) (0.244) (0.230) (0.212) (0.259) (0.277)</td>
</tr>
<tr>
<td>Education Equality Index (log) -1.029 -1.188* -1.326* -1.555** -1.449** -2.485** -3.840***</td>
</tr>
<tr>
<td>(0.688) (0.687) (0.682) (0.631) (0.630) (0.950) (0.885)</td>
</tr>
<tr>
<td>Consump. Gini (log) -0.207 -0.273 -0.293 -0.303 -0.392*</td>
</tr>
<tr>
<td>(0.158) (0.185) (0.197) (0.180) (0.220)</td>
</tr>
<tr>
<td>Fractionalization 0.656** 0.702*** 0.708*** 0.128 0.415</td>
</tr>
<tr>
<td>(0.244) (0.195) (0.207) (0.525) (0.469)</td>
</tr>
<tr>
<td>Prop. in Agr -0.363</td>
</tr>
<tr>
<td>(0.632)</td>
</tr>
<tr>
<td>Prop. in Manuf 4.503</td>
</tr>
<tr>
<td>(3.206)</td>
</tr>
<tr>
<td>Electricity cons. p.c. (log) 0.132</td>
</tr>
<tr>
<td>State exp p. c. (log) -0.0577</td>
</tr>
<tr>
<td>(0.122)</td>
</tr>
<tr>
<td>Time dummies Yes 0.497 0.636 0.751 0.952* 0.805* 1.984*** 3.153***</td>
</tr>
<tr>
<td>(0.566) (0.571) (0.554) (0.518) (0.519) (0.944) (0.995)</td>
</tr>
<tr>
<td>Observations 162 162 162 162 162 90 99</td>
</tr>
<tr>
<td>r2 0.897 0.899 0.907 0.910 0.913 0.939 0.938</td>
</tr>
</tbody>
</table>

Robust standard errors clustered by State in parentheses.  
\(^{*}\) \( p < 0.10, \) \(^{**}\) \( p < 0.05, \) \(^{***}\) \( p < 0.01 \)

In the first column, I only include the mean level of education and the education inequality index. The coefficient on the education equality index is negative,

\(^9\)The choice of nine months is due to data availability.
which shows that the equality of education is negatively correlated to income, but the level of the coefficient is not very precisely estimated. The estimated coefficient on the mean education level is also negative, but one has to keep in mind that it is not the “true” coefficient, because $\ln H$ is also included in the education equality index. The true value of the coefficient is $\beta_1 - \beta_2^{10}$ and is reported at the bottom of table 1.1 along with its standard errors. It is positive but not significant.

In the second column, I add consumption inequality. It is negative but its level is not precisely estimated. However, its inclusion increases the absolute value of the coefficient of the education equality index, which turns significant at a 10% level, showing that the education equality index was actually capturing some income distribution effect.

In the third column the regression is estimated with the mean level of education, the education equality index and the fractionalization index. Unexpectedly, the coefficient of the fractionalization index is positive and significant. This seems to be driven by the North-East States which are very different than the rest of the States in terms of caste composition. When these States are not in the sample, as in column column 6 and 7, the coefficient turns out to be not significantly different from zero. The coefficient of the education equality index is still negative and significant at a 10% level, showing again that the equality index was capturing other distributional effects.

Column (4) confirms the previous findings. When the three variables of distribution are added together, the education equality index is still negative, and significant at a 5% level. Moreover, the coefficient on the mean education level becomes significantly different from zero.

In column (5), (6) and (7), other control variables at the State level are added. In column (5), I add the proportion of individuals working in agriculture and the proportion of people working in manufacture in order to take into account the industrial structure of the economy in the State. The reference group is the service sector. These additional variables are not significant and they neither change the level, nor the significance of the education equality index. It is also important to control for physical capital because it is a strong determinant of income per capita. As no capital data are available at the State level in India, I use the electricity consumption per capita as a proxy in column (6). The data on electricity consumption were missing for several States and are not available for 1983, so the number of observations is dramatically falling in this estimation. The same

10It comes from the fact that $\ln \Gamma = \ln (1 - G_H) - \ln H$.

11The North-East States are very tribal.

12This is the reason why I do not use investment data or electricity consumption as a proxy in every estimation.
problem arises in column (7), with the addition of State expenditures which proxy for the amount spent on education that may be correlated with the structure of the education system and with income per capita. Given the reduction in the number of observations, the coefficients are not strictly comparable. But some results are still worth noting. First, the coefficient of the equality index is still negative and significant, confirming the negative relation between education equality and income per capita. Second, the sign of the consumption Gini is still negative and more precisely estimated. Finally, as mentioned earlier, the coefficient of the fractionalization index is a noisy zero.

Table 1.2: Variable of interest: Theil index estimated with FE

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Net State domestic product per capita</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1) (2) (3) (4) (5) (6) (7)</td>
</tr>
<tr>
<td>Mean Educ (log)</td>
<td>0.331 0.445 0.579 0.747 0.622 1.544 2.906**</td>
</tr>
<tr>
<td></td>
<td>(0.593) (0.604) (0.593) (0.561) (0.564) (1.009) (1.169)</td>
</tr>
<tr>
<td>Theil index</td>
<td>0.849 0.980 1.143 1.338** 1.258* 2.057** 3.634***</td>
</tr>
<tr>
<td></td>
<td>(0.672) (0.677) (0.683) (0.642) (0.639) (0.947) (0.965)</td>
</tr>
<tr>
<td>Consump. Gini (log)</td>
<td>-0.190 -0.255 -0.278 -0.269 -0.437*</td>
</tr>
<tr>
<td></td>
<td>(0.157) (0.182) (0.197) (0.187) (0.213)</td>
</tr>
<tr>
<td>Fractionalization</td>
<td>0.651** 0.694*** 0.701*** 0.160 0.416</td>
</tr>
<tr>
<td></td>
<td>(0.248) (0.203) (0.211) (0.548) (0.487)</td>
</tr>
<tr>
<td>Prop. in Agr</td>
<td>-0.352 (0.627)</td>
</tr>
<tr>
<td>Prop. in Manuf</td>
<td>4.812 (3.151)</td>
</tr>
<tr>
<td>Electricity cons. p.c. (log)</td>
<td>0.147 (0.124)</td>
</tr>
<tr>
<td>State exp p. c. (log)</td>
<td>-0.0678 (0.115)</td>
</tr>
<tr>
<td>Time dummies</td>
<td>Yes Yes Yes Yes Yes Yes Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>162 162 162 162 162 90 99</td>
</tr>
<tr>
<td>r2</td>
<td>0.896 0.897 0.906 0.908 0.912 0.935 0.936</td>
</tr>
</tbody>
</table>

Robust standard errors clustered by State in parentheses.

* p < 0.10, ** p < 0.05, *** p < 0.01

Table 1.2 shows the results when the distribution of education is measured with a Theil index. The Theil index is an indicator of inequality, so we expect the coefficient on this variable to be positive. Table 1.2 confirms the previous results: a more unequal distribution of human capital is associated with a higher income per capita. As using the Theil index does not significantly change the results, in the next tables I only show the results with the education equality index.
5.2 Robustness Checks

Section 4 finds that income per capita and equality of education are negatively related in Indian States. Although I control for State unobservables by estimating the relation with fixed-effects, the point estimate may still be biased if there is selective migration. In the first subsection I discuss the bias induced by migration and in the next subsection I provide evidence that the results are not driven by sample or estimation choices.

5.2.1 Migration

One important endogeneity problem arises if migration affects the distribution of human capital non-randomly, for example if States with higher income per capita attract more educated migrants. In this case, the estimated negative relation between equality of education and income per capita is actually a spurious correlation due to higher educated people migrating to richer States.

Even if I cannot completely rule out this explanation, several facts contradict this idea. First, the rate of migration in India is very low. According to the Indian census of 2001, only 4.7% of the total population of India was born outside of the State of residence. This phenomenon has been studied by Munshi and Rosenzweig (2009) who show that this very low rate of migration is due to the endogamous caste system which provides insurance between households of the same caste. Second, the main reason for migration is marriage. Among migrants,\(^{13}\) 43.8% migrated for marriage, far ahead from the reason “work/employment” (14.7%) or “business” (1.2%). And while people migrating for work may select the State where to migrate depending on its economic strength, there is no obvious reason why this should be the case for marriage motivated migrations.

To complete these arguments, table 1.3 shows some robustness checks related to migration. In column (1), I exclude the three States where the share of total migrants in the population is the highest, namely Maharashtra, Delhi and West Bengal. These three States have respectively 16.4, 11.6 and 11.5% of their population which was born in another State. In column (2) I exclude Delhi and Chandigarh of the estimation. These two “Union Territories” are actually cities with administrative independence, and given that the main type of inter-States migration is from rural to urban area these two States probably attract a lot of migrants. Following the same idea, in column (3) I calculate the education variables (mean and distribution) only with the population living in the rural parts of

\(^{13}\)The census does not give the reasons for migration from the place of birth, so these estimates are for migration from last place of residence and do not differentiate between intra and inter-States migration. The numbers may vary if we only consider inter-States migration.
Table 1.3: Migration robustness checks

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean Educ (log)</td>
<td>-0.517*</td>
<td>-0.566**</td>
<td>-0.468**</td>
</tr>
<tr>
<td></td>
<td>(0.270)</td>
<td>(0.257)</td>
<td>(0.214)</td>
</tr>
<tr>
<td>Education Equality Index (log)</td>
<td>-1.595**</td>
<td>-1.612**</td>
<td>-1.306**</td>
</tr>
<tr>
<td></td>
<td>(0.689)</td>
<td>(0.668)</td>
<td>(0.636)</td>
</tr>
<tr>
<td>Consump. Gini (log)</td>
<td>-0.306</td>
<td>-0.243</td>
<td>-0.276</td>
</tr>
<tr>
<td></td>
<td>(0.192)</td>
<td>(0.206)</td>
<td>(0.182)</td>
</tr>
<tr>
<td>Fractionalization</td>
<td>0.706***</td>
<td>0.731***</td>
<td>0.660***</td>
</tr>
<tr>
<td></td>
<td>(0.201)</td>
<td>(0.201)</td>
<td>(0.185)</td>
</tr>
<tr>
<td>Time dummies</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>$\beta_1 - \beta_2$</td>
<td>1.078**</td>
<td>1.046**</td>
<td>0.837**</td>
</tr>
<tr>
<td></td>
<td>(0.609)</td>
<td>(0.568)</td>
<td>(0.498)</td>
</tr>
<tr>
<td>Observations</td>
<td>144</td>
<td>152</td>
<td>162</td>
</tr>
<tr>
<td>$r^2$</td>
<td>0.901</td>
<td>0.906</td>
<td>0.907</td>
</tr>
</tbody>
</table>

Robust standard errors clustered by State in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

the States. In every specification, the coefficient on the distribution of education is negative, strongly significant, and fairly stable. All together, these robustness checks confirm the fact that if there is an upward bias due to non-random migration, it should be small.

5.2.2 Additional robustness checks

Table 3.4 presents complementary robustness checks. Again, I just present the results with the education equality index. Column (1) uses an alternative panel data method to estimate the relation and columns (2) and (3) are estimated with changes in the sample and in the definition of the variables.

Column (1) presents the estimations with an alternative panel data method, the Blundell and Bond (1998) system GMM which controls for the potential endogeneity of the Consumption Gini and of the Fractionalization Index. The choice of System GMM is made over first-differenced GMM because System GMM performs better when the number of observations is small (Blundell and Bond, 1998), which is the case in this dataset. The methodology of System GMM is as follows: the unobserved heterogeneity between States is controlled for by first-differencing the equation. Then the differenced-equation is instrumented with internal instruments: the differenced endogeneous variables are instrumented by their lagged

---

14 Changes over time in the fractionalization index come from different fertility or mortality across castes. Therefore, the fractionalization index is endogenous if birth or death rates are related to income per capita.
### Table 1.4: Robustness checks

<table>
<thead>
<tr>
<th>Dependent variable: Net State domestic product per capita</th>
<th>(1) System GMM</th>
<th>(2) No NSS 55</th>
<th>(3) 4 levels</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean Educ (log)</td>
<td>0.816***</td>
<td>-0.721***</td>
<td>-0.485**</td>
</tr>
<tr>
<td></td>
<td>(0.278)</td>
<td>(0.229)</td>
<td>(0.191)</td>
</tr>
<tr>
<td>Education Equality Index (log)</td>
<td>-2.024**</td>
<td>-1.869**</td>
<td>-1.134**</td>
</tr>
<tr>
<td></td>
<td>(0.875)</td>
<td>(0.679)</td>
<td>(0.490)</td>
</tr>
<tr>
<td>Consump. Gini (log)</td>
<td>-0.829</td>
<td>-0.313</td>
<td>-0.220</td>
</tr>
<tr>
<td></td>
<td>(0.958)</td>
<td>(0.235)</td>
<td>(0.170)</td>
</tr>
<tr>
<td>Fractionalization</td>
<td>0.724</td>
<td>1.006***</td>
<td>0.653***</td>
</tr>
<tr>
<td></td>
<td>(1.206)</td>
<td>(0.247)</td>
<td>(0.182)</td>
</tr>
<tr>
<td>Time dummies</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>$\beta_1 - \beta_2$</td>
<td>2.840***</td>
<td>1.148***</td>
<td>0.650*</td>
</tr>
<tr>
<td></td>
<td>(0.845)</td>
<td>(0.536)</td>
<td>(0.441)</td>
</tr>
<tr>
<td>AR(1) test</td>
<td>0.790</td>
<td></td>
<td></td>
</tr>
<tr>
<td>AR(2) test</td>
<td>0.684</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hansen J test</td>
<td>0.705</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Diff-in-Hansen test</td>
<td>0.480</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>162</td>
<td>133</td>
<td>162</td>
</tr>
<tr>
<td>N. States</td>
<td>29</td>
<td>29</td>
<td>29</td>
</tr>
<tr>
<td>N. instruments</td>
<td>14</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Instr lags</td>
<td>t-3 to t-4</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Robust standard errors clustered by State in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

values. This differenced equation is simultaneously estimated with the equation in level where the variables are instrumented by their differenced lagged values. The use of this methodology requires three hypotheses to be valid. First, the residuals are uncorrelated at the second order. Second, the lagged values of the control variables must be exogenous to their differenced value. Third, the addition of the equation in level, specific to the System GMM, requires that the differenced lag values of the control variables are uncorrelated with the fixed effects. To ensure the validity of these three hypotheses, various tests are used: the Hansen test of overidentifying restrictions controls for the exogeneity of the whole set of instruments. The difference-in-Hansen test controls for the exogeneity of the instruments used for the equation in level and the Arellano-Bond test indicates the autocorrelation of the residuals. In all the specifications, as there are few time periods, a problem of too many instruments can arise. I therefore collapse the instruments. Only the consumption Gini and the fractionalization index are considered as endogenous because the mean education level and the education equality index are calculated on the more than 15 years old individuals. They are therefore previously determined and the tests do not reject their exogeneity.
The results confirm the findings on the education equality index: it is negatively and significantly related to income per capita. Moreover, in this specification the level of the coefficient is similar to the other specifications in table 1.1. All the control variables have the same sign but only the mean education level is significantly different from zero.

In column (2) the estimation is made without the data from 1999-2000. The questionnaire on consumption for this survey was changed and data are said to be not strictly comparable. Even if it only affects the Consumption Gini variable, as this variable is correlated with the equality index, it might change the results. Again, the results are not affected by this change.

Finally, in column (3) the education variables (mean and equality index) are recalculated with only four levels of education, in order to strictly follow Berthélemy (2006)’s theoretical work. Even if the coefficient on the education equality index is slightly smaller than before, the results broadly confirm the previous findings.

5.3 Non-linearities in the relation between education equality and income per capita?

The results above show a significant and negative association between the equality of education and income per capita. In this section, I check if the level and the direction of the relation depends on the period considered or on the level of development of the State. To preserve the size of the sample, these issues are tested using interaction terms.

I first test if the effect varies over time by creating a dummy variable which is equal to 0 if the education equality index is observed during the three first periods of the sample, that is to say in 1983, 1987-88 and 1993-94 and 1 if the variable is observed in the three most recent periods, in 1999-2000, 2004-05 and 2009-10. The intuition is that the effect of the distribution of education can be different before and after the liberalization that happened progressively from 1991 onwards, in particular because returns to education may have changed during this period. This dummy variable is then interacted with the education equality index. Table 1.5 shows the results.

The results are presented as in table 1.1. I first only include the education variables and I progressively add the other distributional variables. The results are similar to previously. The coefficient on the equality of education index is negative and significant when the other distributional effects are controlled for. The interaction term is negative but not significantly different from zero: it conse-
Table 1.5: Time non-linearities estimated with FE

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Net State domestic product per capita</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1) (2) (3) (4)</td>
</tr>
<tr>
<td>Mean Educ (log)</td>
<td>-0.526* -0.546* -0.569** -0.598**</td>
</tr>
<tr>
<td></td>
<td>(0.276) (0.267) (0.255) (0.241)</td>
</tr>
<tr>
<td>Education Equality Index (log)</td>
<td>-0.924 -1.085 -1.222* -1.456**</td>
</tr>
<tr>
<td></td>
<td>(0.694) (0.695) (0.645) (0.620)</td>
</tr>
<tr>
<td>Educ Equality*After 1999</td>
<td>-0.201 -0.194 -0.196 -0.186</td>
</tr>
<tr>
<td></td>
<td>(0.518) (0.484) (0.570) (0.517)</td>
</tr>
<tr>
<td>Consump. Gini (log)</td>
<td>-0.206</td>
</tr>
<tr>
<td></td>
<td>(0.158)</td>
</tr>
<tr>
<td>Fractionalization</td>
<td>0.656** 0.701***</td>
</tr>
<tr>
<td></td>
<td>(0.253) (0.202)</td>
</tr>
<tr>
<td>Time dummies</td>
<td>Yes Yes Yes Yes</td>
</tr>
<tr>
<td>Joint significance</td>
<td>0.355 0.249 0.173 0.0665</td>
</tr>
<tr>
<td>N</td>
<td>162 162 162 162</td>
</tr>
<tr>
<td>r2</td>
<td>0.898 0.899 0.908 0.910</td>
</tr>
</tbody>
</table>

Robust standard errors clustered by State in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

quently seems that the relation between the education equality index and income per capita is the same during the first ten years than during the most recent ten years.

The second non-linearity test is on the level of development. Does the relation vary depending on the level of income per capita? I test this issue by creating a dummy variable which indicates if the State is over the median or under the median of income per capita. This dummy variable is equal to 0 if the Net Domestic Product of the State in 1999-2000 was inferior to the median Net State Domestic Product this year and 1 otherwise. The date of 1999-2000 is chosen because it is in the middle of the sample.15 This dummy variable is then interacted with the education equality indicator.

Table 1.6 shows the results. Here the results underline a strong heterogeneity in the relation. The coefficient on the interaction term is negative and significant at a 1% level and the coefficient of the education equality index even becomes positive (but only significant in the first specification). Moreover, the p-value for the joint significance of the education equality index and the interaction term (shown under the tables) strongly rejects the null hypothesis that these two coef-

---

15 However, the results hold if the status of the State (over or under the median) is defined at each period with the median of the year.
Table 1.6: Income level non-linearities estimated with FE

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean Educ (log)</td>
<td>-0.226</td>
<td>-0.244</td>
<td>-0.268</td>
<td>-0.294</td>
</tr>
<tr>
<td></td>
<td>(0.268)</td>
<td>(0.257)</td>
<td>(0.260)</td>
<td>(0.244)</td>
</tr>
<tr>
<td>Education Equality Index (log)</td>
<td>0.875*</td>
<td>0.722</td>
<td>0.580</td>
<td>0.362</td>
</tr>
<tr>
<td></td>
<td>(0.513)</td>
<td>(0.520)</td>
<td>(0.592)</td>
<td>(0.554)</td>
</tr>
<tr>
<td>Educ Equality * Over Median</td>
<td>-1.663***</td>
<td>-1.687***</td>
<td>-1.665***</td>
<td>-1.695***</td>
</tr>
<tr>
<td></td>
<td>(0.441)</td>
<td>(0.439)</td>
<td>(0.438)</td>
<td>(0.433)</td>
</tr>
<tr>
<td>Consump. Gini (log)</td>
<td>-0.234*</td>
<td>-0.301*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.127)</td>
<td>(0.151)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fractionalization</td>
<td>0.657**</td>
<td>0.707***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.243)</td>
<td>(0.183)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Time dummies</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Joint significance</td>
<td>0.00187</td>
<td>0.00176</td>
<td>0.00242</td>
<td>0.00143</td>
</tr>
<tr>
<td>N</td>
<td>162</td>
<td>162</td>
<td>162</td>
<td>162</td>
</tr>
<tr>
<td>r2</td>
<td>0.915</td>
<td>0.917</td>
<td>0.925</td>
<td>0.928</td>
</tr>
</tbody>
</table>

Robust standard errors clustered by State in parentheses.

* p < 0.10, ** p < 0.05, *** p < 0.01

Coefficients are jointly zero. Therefore, it seems that education equality in States with a low income per capita is positively correlated to income per capita, whereas in States with a higher income per capita the relation is significantly negative. This result provides a key for reading the results from previous literature. Indeed, when looking at the composition of the samples, it seems that when developing countries are included in the sample, education inequality has a negative impact on growth or income per capita (Lopez et al., 1998; Castelló and Domenech, 2002), whereas when the sample is only composed of developed countries, education inequality has a positive impact (Rodríguez-Pose and Tselios, 2009).

6 Why is the equality of education negatively related to income per capita?

In this section, I explore the channels which may explain the relation of the equality of education with income per capita. In the introduction, I explained three theoretical channels underlined by the literature: return to education, externalities and complementarities.

If we think about income in terms of the output of a production function, the three channels can be related to two different concerns on the production function:
how workers with different levels of education contribute to the production and what is the form of this production function. If workers with different levels of education contribute differently to the production, it means that the marginal return to education of a worker depends on its level of education. In this case the return to education is said to be non-linear and the distribution of education has an impact on income per capita. The form of the production function also determines the impact of the distribution of education. First, workers with different levels of education may be complements or substitutes in the production function. Second, there may be externalities, in which case the productivity of a worker with a given level of education depends on the level of education of its coworkers.

In the rest of the section, the different channels are explained in more details and are tested empirically.

6.1 Complementarity of similar workers in the production function

The first channel that I consider is the channel underlined by Kremer (1993). Kremer (1993) makes the hypothesis that workers with the same amount of human capital are complements in the production function. Therefore, in equilibrium workers with the same education level are matched together in firms. However, this perfect matching depends on the hypothesis that labor markets are perfect and that workers are fully mobile. If there is no perfect mobility, then the distribution of education matters because it affects the probability of workers with a same education level to be matched together.

To test this mechanism, I take advantage of Aghion et al. (2008)’s database which classifies Indian States depending on their labor market regulations. The idea is quite simple: the probability that similar workers are matched together in equilibrium depends on the capacity of the employer to hire similar workers, which in turn depends on labor regulation laws. Therefore, in States were labor market regulations are more pro-worker, I expect a positive relation between the equality of education and income per capita. Relating to my results, as the equality of education has is negatively related to income per capita, I expect that the relation will be less negative in States were labor market regulations are more pro-worker.

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16But this is the third channel described in the introduction.
17This point is not demonstrated by Kremer (1993) but he refers to Becker (1991) for the mathematical proof.
18Crudely, the idea is that if the employer realizes that his workers are not matching, he can easily try to find a better match if labor market regulations are more pro-employer.
The legislation on labor markets in India is principally governed by the Industrial Disputes Act of 1947. However, as industry legislation in India is a competence which is shared between the central government and States government, the legislation has been differently amended by the different States over time. Aghion et al. (2008) in their database code every State amendment as neutral (0), pro-worker (+1) or pro-employer (-1). The scores are then added up on the whole period (1947-1997), in order to have an idea of the regulation direction for each year of the period.

I use this information on labor legislation to study if the relation between the distribution of education and income per capita differs depending on the type of labor regulation. For that, I interact the education equality index with the level of regulation at that year. The coefficient on the interaction term is then estimated as previously, except that the number of periods is reduced to 4 because Aghion et al. (2008)’s dataset stops in 1997. The number of States is also reduced to 17, which leaves us with only 64 observations. Results are shown in table 1.7.

<table>
<thead>
<tr>
<th>Table 1.7: Equality of education and labor regulation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dependent variable: Net State domestic product per capita</td>
</tr>
<tr>
<td>(1) (2) (3) (4)</td>
</tr>
<tr>
<td>Mean Educ (log)</td>
</tr>
<tr>
<td>(0.286)</td>
</tr>
<tr>
<td>Education Equality Index (log)</td>
</tr>
<tr>
<td>(1.163)</td>
</tr>
<tr>
<td>Educ Equality * Labor Regulation</td>
</tr>
<tr>
<td>(0.358)</td>
</tr>
<tr>
<td>Consump. Gini (log)</td>
</tr>
<tr>
<td>(0.328)</td>
</tr>
<tr>
<td>Fractionalization</td>
</tr>
<tr>
<td>(0.550)</td>
</tr>
<tr>
<td>Labor regulation</td>
</tr>
<tr>
<td>(0.316)</td>
</tr>
<tr>
<td>Time dummies</td>
</tr>
<tr>
<td>Joint significance</td>
</tr>
<tr>
<td>N</td>
</tr>
<tr>
<td>r2</td>
</tr>
</tbody>
</table>

Robust standard errors clustered by State in parentheses.
* p < 0.10, ** p < 0.05, *** p < 0.01

Column (1) shows the main results estimated with the reduced sample avail-
Table 1.8: Impact of education equality

<table>
<thead>
<tr>
<th>Type of regulation</th>
<th>Impact size</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pro-employer</td>
<td>-1.828* (0.835)</td>
<td>0.045</td>
</tr>
<tr>
<td>Neutral</td>
<td>-1.227 (1.229)</td>
<td>0.260</td>
</tr>
<tr>
<td>Pro-worker</td>
<td>-0.625 (1.371)</td>
<td>0.655</td>
</tr>
</tbody>
</table>

* p < 0.10. Standard errors clustered at the State level are in parentheses. The coefficients are calculated with the specification of column 3 in table 1.7.

able with Aghion et al. (2008)’s data on labor regulation. The effect is slightly bigger than when estimated with the full sample but it less precisely estimated with a p-value of the coefficient on the equality of education at 10%. The fractionalization index is not anymore significant and becomes negative, which is due to the fact that States from the North East are not included in this reduced sample. Column (2) shows the results with the interaction term. The coefficient of the education equality index is negative and the one of the interaction term is positive. They are both not statistically significant, but they are jointly significant as shown by the p-value reported at the bottom of the table. It therefore seems that *ceteris paribus*, in the States which have more pro-workers regulation (Labor regulation index > 0), the relation of the equality of education with income per capita is less negative.

However, it is a little hard to understand what the coefficients concretely mean, because the labor regulation index takes a large range of value: it goes from -3 to +4. To get a clearer understanding of the relation between education equality and income per capita given a certain regulation level, I simplify the labor regulation index. As States are never moving from a kind of labor regulation to another during the period under study (a State which has a pro-worker regulation never goes to a pro-employer regulation for example), I classify the States into only 3 categories: States which have a pro-employer regulation get a score of -1, States which are neutral have 0 and States which are more pro-worker get +1. The index for a given States is therefore fixed over time. The results with this index are reported in column (3) and table 1.8 calculates the coefficient for the three types of labor regulation. The regression results are similar to the results obtained in column 2. The education equality index is negatively related to income per capita, and the interaction term is positive. Table 1.8 clarifies the relation: when States have a pro-employer regulation, the education equality index is strongly negative and significantly different from zero. However, the coefficient decreases (is less negative) as we move to a less pro-employer regulation, and becomes not significantly different from zero.
Finally in column (4), I use the 6 periods, with the hypothesis that the kind of labor regulation (pro-worker, neutral or pro-employer) did not change in the most recent period. The interaction term is lower but still positive. Given the small number of observations, these results need further confirmation. But they give credit to the complementarity channel.

6.2 Externalities and non-linearity in the return to education

I now explore the two remaining channels, the channel of externalities and the channel of returns to education. These two channels are hard to distinguish, because they have the same cause and the same consequences. Knowledge spillovers go from more educated workers to less educated workers. So given a mean education level, an increase in the share of people with a tertiary education increases income per capita while education equality decreases. The impact is the same if we consider the returns to education channel. As the return curve seems to be convex in India (Duraisamy, 2002), we expect that an increase in the share of people with a higher education increases income per capita while the equality index decreases. Therefore in both cases, the negative relation between the education equality index and income per capita captures the positive impact of an increase in the share of people with a tertiary education given a mean education level.

I consequently consider these two channels together by looking at the impact of adding the proportion of people with a higher education (graduate and above) in the regression. Table 1.9 shows the results.

The first column is the baseline regression. The second column shows the results when the proportion of higher educated people is added. The coefficient is positive and big even though it is not precisely estimated. This positive sign is not surprising: other things being equal, the higher the proportion of highly educated people, the higher income per capita. But what is more interesting is that when this variable is added to the baseline model, the coefficient on the education equality index drops (in absolute value) and becomes not statistically different from zero. It shows that the equality index actually captures some externality or non-linearity effect. To check if this effect is really due to the proportion of highly educated people, in columns (3), (4) and (5) I replace this variable by the proportion of illiterate, primary educated and secondary educated. In those three regressions, the coefficient on the education equality index has the same level than in the first regression and is statistically different from zero. Consequently the proportion of people in the other levels of education does not impact the education equality index. Finally in the sixth column, I add all the education levels, except
Table 1.9: Equality of education and higher education

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>Net State domestic product per capita</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean Educ (log)</td>
<td>(1) Baseline  (2) Higher educ  (3) Illiterate  (4) Primary  (5) Secondary  (6) All levels</td>
</tr>
<tr>
<td>-0.604**</td>
<td>-0.564**</td>
</tr>
<tr>
<td>(0.230)</td>
<td>(0.255)</td>
</tr>
<tr>
<td>Education Equality</td>
<td>-1.555**</td>
</tr>
<tr>
<td>Index (log)</td>
<td>(0.631)</td>
</tr>
<tr>
<td>Consump. Gini (log)</td>
<td>-0.273</td>
</tr>
<tr>
<td>(0.185)</td>
<td>(0.179)</td>
</tr>
<tr>
<td>Fractionalization</td>
<td>0.702***</td>
</tr>
<tr>
<td>(0.195)</td>
<td>(0.196)</td>
</tr>
<tr>
<td>prop higher educ</td>
<td>1.564</td>
</tr>
<tr>
<td>(1.466)</td>
<td></td>
</tr>
<tr>
<td>prop illiterate</td>
<td>-0.611</td>
</tr>
<tr>
<td>(0.822)</td>
<td></td>
</tr>
<tr>
<td>prop primary educ</td>
<td>0.150</td>
</tr>
<tr>
<td>(0.778)</td>
<td>(0.842)</td>
</tr>
<tr>
<td>prop secondary educ</td>
<td>0.179</td>
</tr>
<tr>
<td>(0.919)</td>
<td>(1.148)</td>
</tr>
<tr>
<td>Time dummies</td>
<td>Yes</td>
</tr>
<tr>
<td>(\hat{\beta}_1 - \hat{\beta}_2)</td>
<td>0.952**</td>
</tr>
<tr>
<td>(0.518)</td>
<td>(0.578)</td>
</tr>
<tr>
<td>N</td>
<td>162</td>
</tr>
<tr>
<td>r^2</td>
<td>0.910</td>
</tr>
</tbody>
</table>

Robust standard errors clustered by State in parentheses.
* p < 0.10, ** p < 0.05, *** p < 0.01

for the proportion of illiterate which is the reference level. The results are similar: the presence of the proportion of higher educated people captures the impact of the education equality index.

It consequently seems that some part of the effect of the equality of education is due to the positive impact of the proportion of highly educated people.

7 Conclusion

A huge emphasis has been put on education policies in developing countries in the last ten years, especially thanks to the Millennium Development Goals. In India schooling enrollment rate has now almost reached 100%. There is no more need to prove the beneficial impact of education policies on income and growth. However, the way these education policies should be designed, in terms of which education level should be promoted, is still a matter of debate.

In this paper, my goal is to look at the relation between education inequal-
ity and income per capita in Indian States. I use data from 6 national sample survey rounds between 1983 and 2009-2010. As the Gini of education and the mean education level are highly correlated in each State, I use a methodology proposed by Berthélemy (2006) to separate in the Gini the level effect from the concentration effect. Using fixed-effects and System GMM to estimate the impact, I find that equality of education is negatively related to income per capita and that the relation is stronger in richer States. This result is robust to the use of a Theil index to measure the distribution of education and to the addition of other distribution variables such as a consumption Gini and a fractionalization index. When exploring the channels, I find that the three channels (non-linear returns of education, externalities and complementarities between workers) may be at stake in explaining the negative relation between equality of education and income per capita.

These findings underline important concerns. They show that the way an education system is designed has an impact on the income per capita of a country. It is not only the mean education level which matters but also how it is distributed. This variable is therefore an important omitted variable in the traditional productivity functions and growth regressions. However, the fact that the relation between equality of education and income per capita is not linear also underline that policy makers have to be cautious in their design. The way education should be optimally distributed depends on initial conditions.

This paper consequently opens the way to further research. In particular, it is important to explore additional non-linearities. The relation between the distribution of education and income per capita may for example depend on the production structure of the economy. In addition to have policy relevance, really understanding the relation between distribution of education and income per capita could help clarify the different results found in the literature.
CHAPTER 2

Education spillovers in farm productivity: Empirical evidence from rural India
1 Introduction

The business of private schools is flourishing in India. Between 2005 and 2012, the percentage of 6 to 14 year olds enrolled in private schools rose from 16.3% to 28.3%. These private schools allow for a quick expansion of the education supply, in particular in rural India where the shortage of public schools is important. Indeed, private schools play a compensation role when the State cannot keep up with the fast increase in enrollment. Muralidharan and Kremer (2006) report that poorer States have more private schools per capita than public schools. Apart from filling the gap left by the State, private schools are also preferred by households because they are more effective than public schools in providing knowledge to students. The reasons given for these better results are that the student to teacher ratio is lower in private schools than in public schools and that teachers’ absenteeism is less frequent (Kingdon, 1996; Muralidharan and Kremer, 2006).

This rapid take-off of private schools in India does not go unnoticed and is at the heart of Indian political debates. Most of the discussions are related to this better efficiency and how to provide access to these schools to poor households. However, one important but little debated question is the one of social returns to education. Indeed, if social returns are higher than private ones because of externalities for example, private financing of education is not optimal because individuals invest less in education than what would maximize the welfare of the society.

This paper investigates the existence of social returns to education in India by studying education externalities in agriculture in rural India. Although the rural focus of this study can seem very limited, this geographical restriction is actually relevant for a country like India where almost 70% of the population still lives in rural areas, among which 72% depends on agriculture. Agriculture also accounts for 17% of the GDP, and employs 51% of the total labor force.

Education externalities are not a new idea in the literature (Marshall, 1890; Lucas, 1988). However, because of the identification challenges that they entail, their empirical assessment is quite recent. Theoretically, there are several potential channels leading human capital to have a higher social than private return. The most evident is that an increase in the aggregate human capital of a defined geo-

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1. INTRODUCTION
graphical area can increase productivity above the direct effect of human capital on individual productivity (Moretti, 2004b). It can be due to learning spillovers, if low-skilled workers learn from high-skilled workers, as Martins and Jin (2010) observe from Portuguese firms for example. It can also be due to complementarity effects, as in the O-Ring theory of Kremer (1993) where the human capital of a worker has a marginal return which grows with the human capital of the other workers. Education also has positive externalities if it reduces the probability of getting involved in activities which produce negative externalities such as crime. Another indirect impact of education is through elections, if a more educated electorate takes better decisions on economy-related issues (Moretti, 2004a).

This paper focuses on the direct impact of education on income, by looking at the impact of neighbors’ mean education on households’ farm productivity. Because of the small scale of agricultural production in India, the channel through which neighbors could have an impact on farm productivity is the one of learning spillovers. As farmers are not working together on each other’s farm, there is no room for complementarity as in a firm. But more precisely, what kind of learning can take place? First, farmers can learn from their neighbors about agricultural technology. The fact that there are learning spillovers when there is a technological change has been widely asserted in the literature (see for example in the case of agriculture in developing countries Foster and Rosenzweig, 1995; Munshi, 2004; Conley and Udry, 2010). Neighbors’ education can therefore influence households’ adoption of technologies, through their own adoption of technology, which is related to their education level. It can also have a positive impact on the use of technologies, or more generally, neighbors’ education can increase efficiency in the use of inputs (Weir and Knight, 2007). It can be the case if all farmers are not on the production frontier, which would be a signal that certain inputs, such as fertilizers, manure or grains are over or underused. Finally, neighbors can have an allocative effect: their education level would have an impact on farmers through a learning on which input or output to choose, given their relative prices (Kumbhakar and Lovell, 2003).

The existing empirical literature mainly focuses on education externalities in cities or in firms in developed countries (for the most cited contributions, see Acemoglu and Angrist, 1999; Moretti, 2004c,b). To my knowledge, very few papers study education externalities in agriculture in developing countries, and they suffer from limitations inherent to the study of peer effects, namely the problem of definition of peers, and the identification challenge due to group level unobservables. Appleton and Balihuta (1996), in a first attempt to take into account the
impact of neighbors’ education on agricultural productivity, introduce neighbors’ average level of education in the production function of farmers in rural Uganda. They find that the proportion of farmers with a primary schooling is significantly related to farmers’ productivity. However, the fact that neighbors’ education is calculated at the community level does not allow for the control of omitted community effects. Weir and Knight (2007) estimate average and stochastic production frontier with neighbors’ education as a control variable in rural Ethiopia. Here, neighbors are defined as groups of households within “sites”, so they are able to control for site dummies. They also find a positive relation between neighbors’ education and average production, but they do not find any impact of neighbors’ education on farmers’ efficiency. Again, although some unobservables are controlled for, the strategy does not allow to be conclusive on the causality of neighbors’ education impact. Asadullah and Rahman (2009) use the same methodology to study external returns of education in agriculture in Bangladesh. They control for village fixed effects while defining neighbors at a smaller level called “Bari”.⁴ On the contrary to the two previous papers, they find no evidence of external returns of education on farm productivity. However, the (absence of) results may be driven by the sample design: their database only reports information for two households by Bari. This definition of neighbors allows for village dummies but may be too restrictive to capture any external effect. These three papers underline the trade-off existing in the empirical literature: on one hand, it is necessary to control for geographical fixed effects to prove that the captured effect does not reflect a spurious correlation, but on the other hand, controlling for fixed-effects may lead to too restrictive definitions of neighbors.

The strategy in this paper follows Munshi and Myaux (2006) who exploit the social structure of rural Bangladesh to study the impact of other women’s behavior towards contraceptive on own adoption of contraceptives. They take advantage of the fact that women interact solely within their religious group to define women’s reference group and to rule out that the results are driven by group unobservables.

Here, I exploit a similar context, where social interactions are happening within castes. Although social mobility and social mixing have increased in urban India, life in villages is still organized along caste lines. Education spillovers are therefore expected to occur within caste, while cross-caste effects should be absent. I test this prediction using data from the round 2006 of the ARIS-REDS data, a household survey conducted in rural India. It provides detailed information

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⁴ Each village is composed of several neighborhood called “Baris".

1. INTRODUCTION
about agricultural output for 4641 households in 227 villages distributed across 17 States.

I find that the education level of households from the same caste has a strong impact on farm productivity, but there is no cross-castes effects, and no effects from members from the same caste who do not have agriculture as their main activity. This pattern of results rules out that the estimated education spillover effect is driven by caste-level unobservables. Indeed, as shown by Munshi and Myaux (2006), and reexplained in section 3, these results can only be obtained without any education spillover effect if the omitted determinants of farm productivity are totally uncorrelated across castes, as well as within castes across occupations. This is not likely to be the case as it is argued in section 6.

This paper therefore provides consistent evidence that there is an impact of neighbors’ education when neighbors are adequately defined, and this result is unlikely to be driven by omitted variables. It is however important to keep in mind that the identification relies on the hypothesis previously mentioned, that omitted variables correlated to groups’ educational level and households’ productivity are also correlated within villages and across occupations. If this is not the case, it is possible that the education level of members from the same caste proxies for other caste-level unobservable characteristics, and causality cannot be inferred.

The rest of the paper is organized as follows. Section 2 describes the theoretical framework and the empirical specification. Section 3 discusses the identification challenges and the empirical strategy used. Data and descriptive statistics are provided in section 3 and results in section 4. Finally a discussion on the identification hypotheses is provided in section 6 before concluding in section 5.

2 Education spillovers theoretically and empirically

The goal of this section is to quickly show how education spillovers can be theoretically formalized before describing my empirical specification.

2.1 Theoretical context

Households’ agricultural output is produced according to a Cobb-Douglas production function, where productivity is allowed to depend on neighbors’ education. Namely, output $y$ of household $i$ is produced with three factors of production, land $l$, labor $n$ and physical capital $k$, according to the following specification:
where each household has a specific productivity $A_i$. The external effect of human capital can be captured by allowing $A_i$ to depend on the surrounding human capital, as in Moretti (2004b). In other words, $A_i$ can be written as

$$A_i = f(\bar{E})$$

(2.2)

where $\bar{E}$ is the average human capital in the neighborhood of the household farm. It is important to note that this specification assumes that neighbors’ education augments the productivity of the three factors of production. Whereas other assumptions are possible, neighbors’ education could only increase labor productivity for example, Moretti (2004b) underlines that it is empirically hard to distinguish between all alternative explanations. Moreover, it is likely that in the particular context or agriculture, education spillovers actually increase the productivity of the three factors of production.

### 2.2 Empirical specification

#### 2.2.1 Households’ productivity

Upon taking logs, equation ((2.1)) reads:

$$\ln y_i = \ln A_i + \alpha \ln k_i + \beta \ln n_i + \gamma \ln l_i$$

(2.3)

which can be rewritten as

$$\ln y_i = \alpha \ln k_i + \beta \ln n_i + \gamma \ln l_i + u_i$$

(2.4)

where $u_i = \ln A_i$. Households’ productivity (in log) $\ln A_i$ is therefore the error term of equation (2.4) and can be calculated through the estimation of equation (2.4). Of course, this strategy measures productivity with error. However, given that productivity is afterwards used as a dependent variable, the estimates for the variable of interest should not be biased (Wooldridge, 2003).

Given data availability, $u_i$ is obtained from the estimation of the following equation:

$$\ln y_{is} = \theta + \alpha k_{is} + \beta \ln n_{is} + \gamma \ln l_{is} + D_s + u_{is}$$

(2.5)
I allow for a constant $\theta$. $y_{is}$ is the farm production of household $i$ in state $s$, $k_{is}$ is a dummy variable which is equal to one if the household owns any agricultural equipment, $n_{is}$ is the number of days worked on the land, $l_{is}$ is the amount of land cultivated and $D_s$ are state dummies which take into account the heterogeneity of productivity across states.

### 2.2.2 External effect of education

In a second stage the external effect of education $\delta$ is estimated by regressing the residuals from the estimation of equation (2.4) on neighbors’ education. Neighbors’ education is indexed $cvs$ because it is calculated over people from the same caste $c$ in village $v$ in state $s$. I also allow the aggregate productivity to depend on households characteristics $X_{icvs}$, caste dummies $C_c$, state dummies $d_s$ and a constant $\Theta$.

$$\hat{u}_{icvs} = \Theta + \delta E_{cvs} + X_{icvs} \rho + C_c + d_s + v_{icvs} \quad (2.6)$$

### 3 Identification strategy

Identifying peer effects is a well known empirical challenge (see for example Manski, 1993; Brock and Durlauf, 2001). The three main issues are the endogeneity of network formation, the problem of correlated effects and the reflection problem (Manski, 1993). In section 3.1 and 3.2, I explain how I am addressing the two first issues. The reflection problem is not of concern here. It refers to the fact that if your neighbor influences you, then it is most likely that you also influence your neighbor. But the problem only arises when the group variable considered is a choice variable. It would be problematic for example if I were to look at the impact of neighbors’ use of high-yielding grains on households’ use of high-yielding grains. But here my variable of interest is neighbors’ education level, which is predetermined compared to households’ output.

#### 3.1 Definition of neighbors

The study of peer effects suffers from one important issue which is the endogeneity of network formation (Jackson, 2008). It refers to the problem arising from the fact that people may choose the people with who they interact according to specific characteristics related to the output. In this context for example, if households with a high productivity choose to interact with households with a high education level, the estimate on peers’ education level will be upwardly biased.
The problem of the endogeneity of network formation is here avoided by using a definition of peers which is exogenously determined. Using an exogenous definition of the peer group is a pretty common practice in the literature. However, because of the lack of precise data, the chosen definition is often geographical, such as the village (as in Case, 1992; Foster and Rosenzweig, 1995; Munshi, 2004, for example) or the neighborhood (as in Weir and Knight, 2007; Asadullah and Rahman, 2009). Here, I exploit the social structure of India to define peers, the caste group. As villages in the sample are not situated close to each other, what I call “neighbors” in the rest of the paper are members from the same caste group in the same village.

Caste is defined as an “hereditary, endogamous, usually localized group, having a traditional association with an occupation, and a particular position in the local hierarchy of castes. Relations between castes are governed, among other things by the concepts of pollution and purity, and generally maximum commensality occurs within the caste” (Srinivas, 1962). Although customs and traditions evolve quickly in India, these changes are mostly happening in urban India. In rural India, caste is still the group of reference within which interactions occur. Moreover, within villages, households are often clustered by castes. This characteristics of Indian villages accentuates the concentration of interactions within castes.

Here, households are grouped into four caste groups: the Scheduled Castes (hereafter SC), the Scheduled Tribes (ST), the Other Backward Classes (OBC) and the High Castes. The SC and ST are at the bottom of the hierarchy. The OBC are slightly higher in the hierarchy, but are still considered as low castes. The High Castes as their name indicate are at the top of the hierarchy.

This definition of “neighbors” is of course an approximation of real interactions. It may be that there are households from the same caste who do not influence each other or households from another caste group who have an impact on productivity. Not including in the neighbor’s group households who have an impact or including households who have no impact is similar to a measurement error. But under the hypothesis that the measurement error is uncorrelated to the regressors, the estimates should be downward biased (Wooldridge, 2003).

### 3.2 The problem of group specific omitted variables

The most important problem in this paper is the problem of group specific omitted variables, also called correlated effects in the literature (Manski, 1993). This
problem refers to the situation where the peers variable that we are interested in captures other group level variables that we cannot control for. The identification strategy that I use to deal with this issue is taken from Munshi and Myaux (2006). In their paper, they study the impact of the use of contraception of women from the same community on own use of contraception. They find that the coefficient on the use of contraception of women from the same community is positive and significant, whereas women from the other community in the village have no impact. They argue that this result could only reflect a spurious correlation between unobservables at the community level and contraceptive behavior if unobservables are fully uncorrelated across communities in the same village. In this section, I reproduce their argumentation and I apply it to my own specification. I am therefore closely following their paper.

I first illustrate the problem of omitted variables, by looking at the equation that I estimate. For purposes of clarity, the specification is simplified compared to equation (2.6). In particular, I do not allow for caste dummies or for state dummies, which allows me to drop the \( v \) and the \( s \) index:

\[
\hat{u}_{ic} = \Theta + \delta c E c + \delta o E o + X_{ic} \rho + U c + v_{ic}
\]

(2.7)

where \( \hat{u}_{ic} \) is household’s agricultural productivity, \( E c \) is the average of caste members’ education in the same village, \( X_{ic} \) is individual characteristics and \( U c \) represents the caste level characteristics that we cannot control for in the estimation, because \( U c \) is unobserved. I allow for cross-caste effects by introducing \( E o \), which is the mean education level of village members from other castes. Because interactions are happening within castes, we expect that the education level of households from the same caste has a positive and significant impact, whereas the education level of households from other castes in the village should have no impact. In other words, we expect \( \delta c > 0 \) and \( \delta o = 0 \).

It is easy to see that if there is no impact of neighbors’ education on agricultural productivity, the true specification is:

\[
\hat{u}_{ic} = \Theta + X_{ic} \rho + U c + v_{ic}
\]

(2.8)

In this case, \( E c \) in equation (2.7) proxies for the unobserved \( U c \) if \( E c \) and \( U c \) are correlated. Put differently, a positive estimate of \( \delta c \) when the true value is zero could be obtained if the education level of people from the same caste in the village is correlated to unobserved caste characteristics that have an impact on agricultural productivity. As \( E c \) cannot by itself perfectly proxy for \( U c \), in a model where there is no education spillovers \( E o \) is an additional proxy for \( U c \).
Can we get $\hat{\delta}_c > 0$ and $\hat{\delta}_o = 0$, the expected result from a model with education spillovers, in a model without education spillovers? Yes, but only if $E_o$ does not provide any information on $U_c$. This could only be the case if the unobserved characteristics of members from the same caste and members from other castes in the village, respectively $U_c$ and $U_o$, are orthogonal. Therefore, to explain the pattern where $\hat{\delta}_c > 0$ and $\hat{\delta}_o = 0$ without education spillovers, $U_c$ and $U_o$ must be totally uncorrelated within the village. When estimating equation (2.7), getting $\hat{\delta}_c > 0$ and $\hat{\delta}_o = 0$ consequently rules out that $E_c$, the education level of households from the same caste, captures caste level omitted variables correlated across castes in the village.

However, it does not rule out the case where $E_c$ captures omitted variables which are uncorrelated across caste groups. Even if it is hard to think about unobserved variables correlated to the education level of one caste group and to agricultural productivity but not correlated to the education level of other households in the village as I argue in section 6, this situation should not be excluded. To take that into account, I now estimate the impact of households from the same caste who have agriculture as their main activity, whose education level is $E_{AGRc}$. The other group is members from the same caste who do not have agriculture as their main activity, and their education level is noted $E_{nonAGRc}$. The equation to estimate is:

$$\hat{u}_{ic} = \Theta + \delta_{AGRc}E_{AGRc} + \delta_{nonAGRc}E_{nonAGRc} + X_{ic}\rho + U_{AGRc} + v_{ic}$$ (2.9)

The same reasoning can be applied here. If $\delta_{AGRc} > 0$ and $\delta_{nonAGRc} = 0$, then we can rule out that $E_{AGRc}$ captures the unobserved characteristics $U_{AGRc}$ if $U_{AGRc}$ is not totally uncorrelated with the unobserved characteristics of households from the same caste but not cultivating land $U_{nonAGRc}$. Given the social structure of India, it is really unlikely that there are omitted variables completely uncorrelated within castes. This point is discussed in section 6.

### 4 Data and descriptive statistics

#### 4.1 Data and variables definition

The data used to conduct this study are from the 2006 round of the ARIS-REDS database from the National Council of Applied Economic Research (NCAER). Since 1971, the NCAER has been conducting surveys on a sample of households in 232 villages in the 17 major States of India. The round of 2006 has the advantage to also have a census of every household in each village with basic information.
on households and households’ heads such as their demographic characteristics (gender, age, education level, size of the household) and their main occupation. As detailed information about agriculture is not provided in the census, I have to restrict my analysis to households in the sample who cultivate land. The identification strategy also requires several castes per villages and that in each caste, there are households who do not have agriculture as their main activity. The final sample is therefore composed of 1641 households in 227 villages. Neighbors’ education is calculated using the census.

The first set of variables are the agriculture related variables, used to estimate the production function. The dependent variable is households’ total agricultural output.\(^7\) Most households cultivate several crops, so total output cannot be calculated using quantities. I aggregate the different crops using their value in rupees, declared by the household. When the production function is estimated separately for wheat and rice, total agricultural output is a quantity, measured in quintals.\(^8\) The factors of production are the area of land cultivated (in acres), the number of days worked on the land (this measure includes family workers as well as hired labour), and variables proxying for the capital used, namely mechanized assets and non-mechanized assets. Mechanized assets and non-mechanized assets are dummy variables equal to one if the household respectively owns at least one mechanized,\(^9\) or non-mechanized\(^{10}\) asset. I also control for the proportion of irrigated land and the proportion of land owned (as opposed to rented in) by the household over total land cultivated. When the productivity is estimated separately for wheat and rice, because I do not have the precise information per crop, the variable for irrigation is just a dummy equal to one if the land on which the crop is cultivated is irrigated, and the variable for land ownership is also a dummy variable equal to one if the land is owned by the household.

The second set of variables used is household level demographic characteristics, namely the age of the household head, her/his gender, her/his education level (in years of schooling) and the number of members in the household. There are also dummies indicating the caste group of the household. Neighbors’ education

---

\(^7\)I only focus on field crops. Plantation crops, such as coffee or tea are excluded, to keep some homogeneity in my sample. It is however not a strong restriction because only six households in the data cultivate plantation crops.

\(^8\)One quintal is 100 kg.

\(^9\)Mechanized assets include tractors, trailers, threshers, electrified motors, non-electrified motors (oil engine), gauge wheels, ploughs, tractors with trailer, tractors with thresher, tractors with oil engine, tractors with gauge wheel, tractors with plough, disc harrows, tillers or cultivators, plough discs or mould boards seed drills, power tillers, power sprayers, chaff cutters, cane crushers, combine harvesters.

\(^{10}\)Non-mechanized assets include iron ploughs, cultivators, harrows, levelers, hoes or manual earth removers, seed rills, weeders, sprayers or dusters, winnowers or pitch forks, bullock carts, chaff cutters, sickles, scissors.
level, depending on the specification, is the mean education level of households’ heads from the same caste in the village or the mean education level of households’ heads from the same caste who have agriculture as their main occupation. In both cases, the education level of the household’s head is excluded from the mean calculation.

4.2 Descriptive statistics

Table 4.2 reports descriptive statistics for the whole sample of households having agricultural output. In mean, the head of the household is around fifty years old and has primary education (5 years of education). Only 5% of the households’ heads are women and a household is composed on average of 6 people. In terms of agricultural equipment, only a third of the households have a mechanized asset but almost every household has at least one non-mechanized asset (96%). Interestingly, a big proportion of land which is cultivated is owned by the household and is irrigated. Also, new technologies are widely used: 63% of the households have at least one crop for which they are using high yielding varieties (thereafter HYV).

However, when we look at the statistics separately by caste, the situation is very heterogenous across caste groups. Although pure demographic characteristics such as age, household size, and percentage of households with a female head do not differ strongly from one group to the other, the other variables such as education or cultivated areas are very different and follow the traditional hierarchy. Scheduled castes and scheduled tribes have a lower education level and cultivate less land than OBC, who are themselves worse-off than high castes. Similarly the proportion of low caste land which is irrigated or the probability that a low caste has mechanized equipment is much lower than for a high caste. The fact that human capital and wealth is distributed along caste lines is not very surprising. It is a widely reported phenomenon in the literature (see e.g. Kijima, 2006). These statistics confirm that in rural India, the economic situation is still highly related to the caste one is born in.

I now turn to the descriptive statistics for neighbors. As a reminder, neighbors’ characteristics are calculated with the data that provide information for every household in the village (what is called the census). The first set of neighbors’ descriptive statistics is when neighbors are defined as members from the same caste, whatever the occupation. We can see that neighbors are slightly different than the sample of farmers. They have smaller households, and a lower education level in mean. Reassuringly, when we only look at neighbors with farming as their main activity, neighbors are really similar to the sample of farmers. The only
## Table 2.1: Descriptive statistics

<table>
<thead>
<tr>
<th></th>
<th>Full sample</th>
<th>SC</th>
<th>ST</th>
<th>OBC</th>
<th>High castes</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Households’ demographic characteristics</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age (Years)</td>
<td>50.87</td>
<td>50.34</td>
<td>52.56</td>
<td>50.43</td>
<td>52.56</td>
</tr>
<tr>
<td>Household Size</td>
<td>6.09</td>
<td>5.79</td>
<td>6.23</td>
<td>6.85</td>
<td>6.50</td>
</tr>
<tr>
<td>Female head</td>
<td>0.05</td>
<td>0.06</td>
<td>0.05</td>
<td>0.06</td>
<td>0.05</td>
</tr>
<tr>
<td>Years of schooling</td>
<td>5.14</td>
<td>4.04</td>
<td>4.04</td>
<td>5.04</td>
<td>6.04</td>
</tr>
<tr>
<td><strong>Farms’ characteristics</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cultivated area (in acres)</td>
<td>6.90</td>
<td>3.67</td>
<td>6.23</td>
<td>6.85</td>
<td>8.66</td>
</tr>
<tr>
<td>Days worked on field</td>
<td>129</td>
<td>95</td>
<td>95</td>
<td>129</td>
<td>152</td>
</tr>
<tr>
<td>% Mechanized assets</td>
<td>0.33</td>
<td>0.12</td>
<td>0.15</td>
<td>0.32</td>
<td>0.46</td>
</tr>
<tr>
<td>% Non-mechanized assets</td>
<td>0.96</td>
<td>0.96</td>
<td>0.98</td>
<td>0.98</td>
<td>0.98</td>
</tr>
<tr>
<td>Proportion of land owned</td>
<td>0.93</td>
<td>0.88</td>
<td>0.98</td>
<td>0.92</td>
<td>0.92</td>
</tr>
<tr>
<td>% HYV</td>
<td>0.64</td>
<td>0.57</td>
<td>0.43</td>
<td>0.68</td>
<td>0.68</td>
</tr>
<tr>
<td><strong>Neighbors’ characteristics</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All neighbors</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean age</td>
<td>49.12</td>
<td>47.20</td>
<td>47.92</td>
<td>48.55</td>
<td>50.92</td>
</tr>
<tr>
<td>Mean HH size</td>
<td>5.61</td>
<td>5.29</td>
<td>5.47</td>
<td>5.68</td>
<td>5.65</td>
</tr>
<tr>
<td>% of female head</td>
<td>0.09</td>
<td>0.10</td>
<td>0.09</td>
<td>0.08</td>
<td>0.09</td>
</tr>
<tr>
<td>Mean education level</td>
<td>4.61</td>
<td>5.61</td>
<td>5.47</td>
<td>5.68</td>
<td>5.65</td>
</tr>
<tr>
<td>Neighbors cultivating land</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean age</td>
<td>50.54</td>
<td>50.76</td>
<td>48.61</td>
<td>50.17</td>
<td>51.50</td>
</tr>
<tr>
<td>Mean HH size</td>
<td>5.89</td>
<td>5.67</td>
<td>5.74</td>
<td>5.97</td>
<td>5.97</td>
</tr>
<tr>
<td>% of female head</td>
<td>0.06</td>
<td>0.07</td>
<td>0.07</td>
<td>0.06</td>
<td>0.07</td>
</tr>
<tr>
<td>Mean education level</td>
<td>4.79</td>
<td>3.74</td>
<td>3.74</td>
<td>4.59</td>
<td>4.59</td>
</tr>
</tbody>
</table>

The table reports the means for each variable and standard deviations are in parentheses.
difference is on the education level that is lower for farmers. It may be due to the fact that the definition of farmers is different in the sample and in the census. While in the sample a farmer is anybody who has some agricultural output, in the sample farmers are only those who have agriculture as their main activity.

5 Results

5.1 Productivity estimation

The first step, before estimating the impact of neighbors’ education, is to get the farm productivity of each household. To do that, I estimate equation (2.5) and take the residuals. The results from the estimation is reported in column 1 of table 2.2. The subsequent columns show the estimation of the productivity equation for wheat (column 2) and for rice (column 3). The samples in those columns are therefore restricted to households cultivating wheat and rice respectively.

<table>
<thead>
<tr>
<th>Table 2.2: Productivity estimation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dependant variable: Total agricultural output</td>
</tr>
<tr>
<td>Cultivated area (in log)</td>
</tr>
<tr>
<td>Days worked (in log)</td>
</tr>
<tr>
<td>% Mechanized assets</td>
</tr>
<tr>
<td>% Non-mechanized assets</td>
</tr>
<tr>
<td>Irrigated land</td>
</tr>
<tr>
<td>Land owned</td>
</tr>
<tr>
<td>State dummies</td>
</tr>
<tr>
<td>N</td>
</tr>
<tr>
<td>r²</td>
</tr>
</tbody>
</table>

* p < 0.10, ** p < 0.05, *** p < 0.01. Robust standard errors are reported in parentheses. The dependent variable in column 1 is total production, in column 2 it is wheat production and in column 3 it is rice production. Some people neither cultivate wheat nor rice, so the number of observations in column 2 and 3 do not sum up to the number of observations in column 1.
The results are very similar in the three columns. The $R^2$ is very high: the variables explain up to 85% of the variation in output. Not surprisingly, land is the most important factor of production, followed by labor. Having irrigation also seems to matter a lot. The reason why the coefficient on irrigation is very different once the estimation is made separately for wheat and rice is because the variable is not measured the same way.\footnote{See section 3 for an explanation on the variables construction.} Finally, owning the land which is cultivated instead of renting does not seem to matter for productivity.

5.2 Caste and cross-caste impact

The residuals of equation (2.5) are now used as a measure of households’ productivity. I look at the impact of the education of members from the same caste and of the education of the other castes in the village. All the regressions are estimated with state dummies. The first set of results is in table 3 column 1 to 3. In column 1, the only control variables are the household demographic characteristics. In column 2, I add control variables at the caste in the village level, namely the number of caste members in the village and the caste mean value of households characteristics (mean age of households’ heads, percentage of female heads in the caste, and mean household size). In column 3, I additionally control for the same variables calculated over members of the other castes in the village. The results are very stable across specifications and robust to the addition of caste level controls. I find that the mean level of education of members from the same caste in the same village is strongly positive and significant: an additional year in the mean level of education of caste-mates increases household productivity between 5.5 and 6.1%. On the contrary, the education level of members from other castes in the village has no impact. In the three specifications, the coefficient is close to zero and not significant.

For the other variables, the only household’s characteristic which has an impact on productivity is households’ size. For a given quantity of labor, having more family members increases productivity. It can be due to hired labor being less productive than family members, which is in line with what Rosenzweig and Foster (2010) find for India. Surprisingly, the head’s education has no impact. Although it can be a mechanical effect due the external effects of education,\footnote{Weir and Knight (2007) underline that the effects of education may not be apparent if less educated farmers copy more educated farmers} an alternative explanation is that households’ heads education and neighbors education are substitutes. Indeed, when the education of members from the same caste is not included (not reported here), the household’s head education has a
### Table 2.3: Within villages: caste and cross-caste effect

<table>
<thead>
<tr>
<th>Dependant variable</th>
<th>Household Productivity</th>
<th>Placebo</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Age (Years)</td>
<td>0.000863</td>
<td>0.000976</td>
</tr>
<tr>
<td></td>
<td>(0.000654)</td>
<td>(0.000637)</td>
</tr>
<tr>
<td>Female head</td>
<td>-0.0126</td>
<td>-0.0137</td>
</tr>
<tr>
<td></td>
<td>(0.0394)</td>
<td>(0.0376)</td>
</tr>
<tr>
<td>Household Size</td>
<td>0.00819***</td>
<td>0.00710***</td>
</tr>
<tr>
<td></td>
<td>(0.00289)</td>
<td>(0.00246)</td>
</tr>
<tr>
<td>Head education level</td>
<td>0.00194</td>
<td>0.00202</td>
</tr>
<tr>
<td></td>
<td>(0.00200)</td>
<td>(0.00198)</td>
</tr>
<tr>
<td>Scheduled Caste</td>
<td>0.114</td>
<td>0.142</td>
</tr>
<tr>
<td></td>
<td>(0.0891)</td>
<td>(0.0894)</td>
</tr>
<tr>
<td>Scheduled Tribe</td>
<td>0.232**</td>
<td>0.261***</td>
</tr>
<tr>
<td></td>
<td>(0.101)</td>
<td>(0.0995)</td>
</tr>
<tr>
<td>Other Backward Classes</td>
<td>0.116**</td>
<td>0.118**</td>
</tr>
<tr>
<td></td>
<td>(0.0566)</td>
<td>(0.0563)</td>
</tr>
<tr>
<td>Caste mean education level</td>
<td>0.0546***</td>
<td>0.0614***</td>
</tr>
<tr>
<td></td>
<td>(0.0168)</td>
<td>(0.0172)</td>
</tr>
<tr>
<td>Head educ * Caste mean education</td>
<td>-0.00356**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00149)</td>
<td></td>
</tr>
<tr>
<td>Other castes mean education level</td>
<td>-0.000170</td>
<td>-0.00176</td>
</tr>
<tr>
<td></td>
<td>(0.0156)</td>
<td>(0.0156)</td>
</tr>
<tr>
<td>State dummies</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Caste controls</td>
<td>no</td>
<td>yes</td>
</tr>
<tr>
<td>Other caste controls</td>
<td>no</td>
<td>no</td>
</tr>
<tr>
<td>N</td>
<td>4641</td>
<td>4641</td>
</tr>
<tr>
<td>r2</td>
<td>0.0341</td>
<td>0.0430</td>
</tr>
<tr>
<td>Head educ &amp; interact</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Head educ &amp; Caste educ</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Impact for caste educ</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Head educ: 0 years</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Head educ: 5 years</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Head educ: 10 years</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Head educ: 15 years</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

* p < 0.10, ** p < 0.05, *** p < 0.01. Robust standard errors in parentheses, corrected for clustering at the caste in the village level. Caste controls and other caste controls include the number of people in each group and the mean value for the demographic characteristics (age, proportion of female head, household size). P-values for the joint significance between the head education level and the interaction term and between caste mean education level and the interaction term are reported. The bottom of the table also reports the marginal impact of caste education for various values of the head education.

Positive and significant impact. In column 4, I test this explanation by interacting neighbors’ education with households’ head education. The interaction terms...
turns out to be negative, which underlines that neighbors’ education and heads’ education are substitute: the positive impact of neighbors’ education decreases with households’ heads education. For example, an additional year of education in castes’ mean education level increases households’ productivity when the head has no education by 7%. However, when the head has a university diploma (15 years of education), neighbors do not matter anymore. Reassuringly, with this specification, education also has a private return.

So far, the results in table 2.3 have shown that there is a positive impact of neighbors’ education on households’ productivity. The fact that the education of other castes has no impact on households’ productivity rules out that the estimated caste effect is driven by unobserved caste variables correlated across castes as explained in section 3.2. However, one can still think that the impact is due to unobserved caste variables uncorrelated across castes. For example, the fact that castes are geographically clustered in villages may lead to this kind of spurious correlation. It can be that schools settle in the most prosperous areas of villages, in which case castes situated in those areas have an easier access to education, as well as a higher productivity.

To test if this is this kind of unobservable uncorrelated across castes that is driving the impact, column 5 presents the results of a falsification test, where the dependent variable is households’ savings. There is arguably no education spillovers effects in savings behavior, notably because the amount that households save is hardly observable by their neighbors. There is indeed empirical evidence that households in developing countries develop strategic behaviors to hide their savings, in order to avoid “taxation” from their network (Baland et al., 2011; Di Falco and Bulte, 2011). However, we can think that savings are correlated to other caste level variables, such as caste wealth. Therefore, if the positive impact of neighbors’ education on productivity was driven by unobservables at the caste level, then we would expect that the coefficient on neighbors’ education in the falsification test is also positive and significant. But the results in column 5 confirm the interpretation of the positive coefficient on caste members education as an education spillover effect: the amount of savings is not affected by caste members’ education.

---

13Insurance mechanisms have been observed to happen within castes (Munshi and Rosenzweig, 2009), which means that households savings may be affected by the other caste members income or wealth.
5.3 Within castes: same occupation and cross-occupation effect

The results in section 5.2 show a positive impact of caste members’ education on households’ productivity. The fact that the education level of households not from the same caste in the village has absolutely no impact and the falsification test underline that the results do not seem to be driven by caste level unobservables.

As explained in section 3.2, an alternative way to check if the measured spillovers comes from unobservables correlated to caste’s education and productivity is to only focus on households from the same caste. Caste members are now divided between those who have agriculture as their main activity and the others. As underlined in the introduction, the channels leading to education spillovers in agriculture are related to agriculture so we do not expect education spillovers to go from households not having agriculture as their main occupation to households having agriculture as their main occupation. The interpretation of the results is as previously. If there is no cross-occupation impact, then we can rule out that the coefficient on neighbors’ education reflects a spurious correlation due to unobserved characteristics uncorrelated across occupations within caste.

Table 2.4 shows the results. They are organized as in table 2.3: column 1 shows the main specification. Although I control for households’ characteristics as in table 2.3, their coefficients are not reported because they do not provide additional information. Again the results are consistent with an education spillover effect: households from the same caste who have agriculture as their main activity have a strong and significant impact on households’ productivity. An increase of one year in their mean education level increases household’s productivity between 4.3 and 4.8%. On the contrary, the variable which measures the education level of neighbors from the same caste but who are not farmers has no impact: the coefficient is very close to 0 and not significant.

Columns 2 and 3 test the robustness of these results by adding additional caste-occupation level controls. The results are very robust. There is a strong impact from households who cultivate land whereas those who do not have no impact. Column 4 looks at the complementarity between head’s education and neighbors education. Again, it seems that households’ heads education and neighbors education are substitutable: the impact of neighbors’ education diminishes with households’ level of education. Finally column 5 runs the same falsification test as in table 2.3 with households’ savings as the dependent variable. There is no impact of neighbors’ education on savings. This result, along with the absence of cross-occupation impact reinforces the argument that the previously measured impact of neighbors’ education is not driven by unobservables.
Table 2.4: Within caste: same occupation and cross-occupation effect

<table>
<thead>
<tr>
<th>Dependant variable:</th>
<th>Household Productivity</th>
<th>Placebo</th>
</tr>
</thead>
<tbody>
<tr>
<td>Head education level</td>
<td>0.00221 (0.00202)</td>
<td></td>
</tr>
<tr>
<td>Same occup caste mean education level</td>
<td>0.0429*** (0.0146)</td>
<td></td>
</tr>
<tr>
<td>Head educ * caste agr mean education level</td>
<td>-0.00298 (0.00128)</td>
<td></td>
</tr>
<tr>
<td>Other occup caste mean education level</td>
<td>0.00590 (0.0130)</td>
<td></td>
</tr>
<tr>
<td>HH controls yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>State dummies yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Caste occup controls no</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Caste oth occup controls no</td>
<td>no</td>
<td>yes</td>
</tr>
<tr>
<td>N</td>
<td>4641</td>
<td>4641</td>
</tr>
<tr>
<td>r2</td>
<td>0.0318</td>
<td>0.0388</td>
</tr>
<tr>
<td>Head educ &amp; interact</td>
<td>0.0366</td>
<td></td>
</tr>
<tr>
<td>Interact &amp; Caste educ</td>
<td>0.0009</td>
<td></td>
</tr>
</tbody>
</table>

Impact for caste educ
- Head educ: 0 years 0.0641***
- Head educ: 5 years 0.0492***
- Head educ: 10 years 0.0343**
- Head educ: 15 years 0.0194

*p < 0.10, **p < 0.05, ***p < 0.01. Robust standard errors in parentheses, corrected for clustering at the caste in the village level. Caste occup controls and caste oth occup controls include the number of people in each group and the mean value for the demographic characteristics (age, proportion of female head, household size). P-values for the joint significance between the head education level and the interaction term and between caste age mean education level and the interaction term are reported. The bottom of the table also reports the marginal impact of caste age education for various values of the head education.

5.4 Who benefits from education spillovers? Heterogeneity across crops

On average, there is an education spillover effect. The mean education level of households from the same caste and from the same occupation has a positive impact on agricultural productivity. However, in section 5.2 and 5.3, I do not differentiate across crops, even if there are good reasons to believe that the impact differs. The extent to which learning can happen for a specific crop may depend on the difficulty to cultivate this crop, as well as the level of technology used for cultivation. In this section, I look at the impact of neighbors’ education separately for two crops, rice (paddy) and wheat.

Rice and wheat are the two main crops cultivated in India. In my sample,
27% of the households only cultivate wheat, 31% only cultivate rice and 21% cultivate both. Therefore only 21% cultivate neither wheat nor rice. Additionally, except for the States on the western ocean side (Andhra Pradesh, Orissa, Tamil Nadu and West Bengal) and Kerala where there is no wheat cultivated, most of the States cultivate both crops.\textsuperscript{14} These two crops have seen a huge increase in their productivity during Green Revolution which began at the beginning of the 70s, thanks to the diffusion of HYV. However, the process of adoption has been slower for rice, because the productivity of the first generation of rice HYV was very dependent on local conditions. Munshi (2004) shows that learning from neighbors was lower for rice HYV than for wheat HYV during the Green Revolution. This finding is also consistent with the papers previously quoted on education spillovers, although the grain type is not given as a possible explanation of the differences in findings. Appleton and Balihuta (1996) and Weir and Knight (2007), study education spillovers respectively for agricultural productivity in general\textsuperscript{15} and cereals productivity, and they do find that there is an impact. On the contrary, Asadullah and Rahman (2009) look at the impact of education spillovers on rice productivity and do not find any evidence that neighbors’ education matter. One can think that it is due to the smaller learning potential in rice production.

Table 2.5 provides independent estimations for rice and wheat. As previously, the dependent variable is household’s productivity, which is the residual taken from the separate estimation for rice and wheat of equation (2.5). In column 1 and 3, I report the results for the main specification. The impact of neighbors’ education is indeed different for wheat and rice. For wheat, the impact is big and similar to what was previously measured, the impact is smaller for rice and only significant at the 10% level. The results are also different for the impact of the household head’ education. For wheat, similarly to the aggregate productivity, there seems to be no impact of households’ own education. On the contrary, for rice the education of households’ heads is positive and significant. This result is in line with Munshi (2004), who finds that there is learning from neighbors for wheat, but that rice growers experiment more on their own land to compensate for the lack of learning.

However, in Munshi (2004), the absence of learning from neighbors for rice was specifically related to HYV adoption. The impact of neighbors’ education should consequently differ depending on wether the farmer is using HYV or traditional grains. To test the hypothesis that the lower impact for rice is related to the

\textsuperscript{14}Rajasthan is an exception: in my sample only 2 households cultivate rice. Therefore it is excluded from the rice estimation.

\textsuperscript{15}The production of the different crops is aggregated.
### Table 2.5: Impact for wheat and rice

<table>
<thead>
<tr>
<th>Crop</th>
<th>(1) Wheat</th>
<th>(2) Wheat</th>
<th>(3) Rice</th>
<th>(4) Rice</th>
</tr>
</thead>
<tbody>
<tr>
<td>Head education level</td>
<td>0.00241</td>
<td>0.00211</td>
<td>0.00732***</td>
<td>0.00724***</td>
</tr>
<tr>
<td></td>
<td>(0.00217)</td>
<td>(0.00214)</td>
<td>(0.00214)</td>
<td>(0.00213)</td>
</tr>
<tr>
<td>Same occup caste mean</td>
<td>0.0372***</td>
<td>0.0361**</td>
<td>0.0238</td>
<td>0.0449***</td>
</tr>
<tr>
<td>education level</td>
<td>(0.0119)</td>
<td>(0.0149)</td>
<td>(0.0131)</td>
<td>(0.0154)</td>
</tr>
<tr>
<td>Other occup caste mean</td>
<td>0.00491</td>
<td>0.00732</td>
<td>-0.00633</td>
<td>-0.00841</td>
</tr>
<tr>
<td>education level</td>
<td>(0.00955)</td>
<td>(0.00922)</td>
<td>(0.0130)</td>
<td>(0.0129)</td>
</tr>
<tr>
<td>HYV</td>
<td>-0.0595</td>
<td></td>
<td>0.244***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0828)</td>
<td></td>
<td>(0.0873)</td>
<td></td>
</tr>
<tr>
<td>Caste educ* HYV</td>
<td>-0.00208</td>
<td></td>
<td>-0.0317***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0138)</td>
<td></td>
<td>(0.0140)</td>
<td></td>
</tr>
<tr>
<td>HH controls</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>State dummies</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Caste occup controls</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Caste oth occup controls</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>N</td>
<td>2210</td>
<td>2207</td>
<td>2415</td>
<td>2408</td>
</tr>
<tr>
<td>r2</td>
<td>0.0569</td>
<td>0.0608</td>
<td>0.0557</td>
<td>0.0645</td>
</tr>
<tr>
<td>HYV &amp; interact</td>
<td>0.0669</td>
<td>0.0170</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Interact &amp; Caste educ</td>
<td>0.0098</td>
<td>0.0648</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Impact for caste educ

| HYV = 0   | 0.0361** | 0.0449*** |
| HYV = 1   | 0.0340***| 0.0132    |

*p < 0.10, ** p < 0.05, *** p < 0.01. Robust standard errors in parentheses, corrected for clustering at the caste in the village level. Casteoccup controls and casteothoccup controls include the number of people in each group and the mean value for the demographic characteristics (age, proportion of female head, household size). P-values for the joint significance between cultivating HYV and the interaction term and between caste age mean education level and the interaction term are reported. The bottom of the table also reports the marginal impact of caste age education when grains are HYV and when they are not.

Technology used, in column 2 and 4, I interact neighbors’ education with a dummy variable equal to one if the household is using HYV grains. For wheat, the impact of neighbors’ education does not depend on the technology used. The interaction term between neighbors’ education and using HYV grains is not significant and very close to zero. However, for rice, the results confirm that learning depends on the type of technology used. When households use traditional grains, neighbors have a strong and significant impact: a one year increase in neighbors’ education increases rice productivity by 4.5%. But when the household is using HYV, the coefficient on neighbors’ education is small and not significantly different from zero (bottom line of table 2.5). This result underlines that education spillovers are in mean smaller for households who produce rice because there is no, or very
little learning happening for households using rice HYV grains.

6 Discussion

Section 4 shows that the mean education level of households from the same caste and having agriculture as their main activity is positively correlated to households’ farm productivity. This result can be interpreted as causal if there is no group level unobservables affecting both households’ productivity and castes’ mean level of education. Moreover, given that households not from the same caste and households from the same caste but who do not have agriculture as their main activity have no impact on households’ productivity, even if there are caste level unobservables, the relation is not causal only if those unobservables are fully uncorrelated across castes, and within castes across occupations, as explained in section 3.2. In this section I discuss the likelihood that castes’ mean education level is correlated to castes level unobservables having an independent impact on productivity, and consequently the likelihood that this variable captures other effects that education spillovers.

The mean education level of a caste in an area depends on the supply of education, as well as the demand for education of this caste. It is very unlikely that the results are driven by a supply side story. Indeed, getting the results of table 2.3 without spillovers effects would require that the unobservables that are correlated to castes mean education level and households’ productivity are totally uncorrelated across castes. All the variables that one can think of that would have an impact on the supply of education, are correlated within villages. For example, the presence of a school in the village, the distance to the closest city or schooling quality are correlated across castes within villages. Desai and Kulkarni (2008) however report that in some villages, scheduled castes are not allowed to cross higher castes areas and consequently that dalit children have a very long way to go to school, because they have to walk along the periphery of the village. This kind of discrimination could create artificial differences in the education supply for different castes within a village. But even if this is the case, it is hard to imagine that the supply of education is fully uncorrelated within castes. There is no particular reason why a scheduled caste child whose family cultivates land has a better access to schooling than a scheduled caste child whose family has another occupation. No supply side explanations could explain the pattern of results that I get in table 2.4.

On the demand side, the situation is more complex. Demand for education depends on several things, such as ability, wealth of the family, or expected returns.
to education. Whereas there are good reasons to believe that ability is randomly distributed across castes and occupations, wealth and returns to education may be more problematic. It is well reported that wealth is still distributed along castes line in India, and that low castes have a lower return to education (Kijima, 2006). It is possible to imagine that wealth and returns to education are totally uncorrelated across castes in a village. The fact that I add caste dummies in my specification may mitigate the problem because it controls for the unobservables which are common to all members from the same caste. In particular, it controls for the hierarchy across castes, which is at the origin of the distribution of wealth and opportunities along castes lines. Moreover, for caste wealth and caste expected returns to education to generate a spurious correlation, they also need to be correlated to land productivity in some way. That would be the case if castes in less fertile areas invest less in education, because they are poorer due to the low fertility of their land. However, it is not highly probable that land quality is fully uncorrelated within a same village. Most of the variation of land quality is from one village to the other. The final argument against explaining the results by systematic differences in terms of wealth and educational returns, comes from the results obtained in table 2.4 which shows that there is no impact of members from the same caste who do not have agriculture as their main activity. Again, given this result, for the positive impact of caste’s mean education level to be driven by unobservables, unobservables must be totally uncorrelated within castes. Wealth and educational returns are in fact two determinants of the educational demand which have been shown to be correlated within castes, because of insurance mechanisms (Munshi and Rosenzweig, 2006), and networks effects for accessing jobs (Munshi and Rosenzweig, 2009).

7 Conclusion

This paper takes advantage of the social structure in India to study spillovers of education in farm productivity. The results show that the mean education level of education of members from the same caste is positively related to households’ productivity. On the contrary, there is no cross-caste effect. The results also show that within castes, only households who have agriculture as their main activity have a positive impact on households’ productivity. This pattern of results helps ruling out that the measured impact is a spurious correlation due to unobservable characteristics. Additionally, this paper shows that spillovers are higher for wheat than for rice, which is consistent with the fact that learning from neighbors is restricted when growing conditions strongly depend on land characteristics.
These findings confirm that education externalities do not only exist in urban contexts and education spillovers do not only occur between workers of the manufacturing and service sectors. There are also spillovers in more traditional sectors such as agriculture. Therefore, improving education in developing countries should continue to be a priority, because education has a multiplicative effect, even in rural areas. However, the fact that the external effect of education seems to be happening solely within social groups reinforces the fact that equality of access to education across social groups is even more important. In India, the law imposing that 25% of classroom seats should be reserved for children from poorer or disadvantaged families in the neighborhood goes into that direction.

These findings also have implications for other developing countries, where school enrollment is low and inequality across ethnic groups is also very salient.
CHAPTER 3

Stigma in affirmative action application? Evidence from quotas in education in India
1 Introduction

Social policies designed to reduce poverty often suffer from low take-up (Currie, 2006). Aizer (2007) for example underlines that half a million children in the United States did not have health insurance whereas they could benefit from Medicaid. Riphahn (2001) finds that 60% of the households eligible for transfers under the German social assistance program did not claim their benefits. Low take-ups can have dramatic consequences in terms of poverty reduction. If people eligible to social programs do not apply, even policies which have proved to be helpful to the poor once they benefit from it will not succeed to alleviate poverty. Understanding the determinants of social programs participation is therefore key to poverty reduction and development in general.

Although not taking the benefits of a social program can appear on a first sight as an irrational behavior, several explanations have been suggested. First, it can come from poor information on the program (Aizer and Currie, 2004). For example, it is possible that people are not aware of the existence of the program, or do not know how to benefit from it. Second, transaction costs may be too high (Bitler et al., 2003; Aizer, 2007). If the procedure to apply is very long or complicated, it is very likely that take-up rates will be low. Finally, eligible people may not apply to avoid the stigma attached to the policy, where stigma is defined as “the disutility arising from the participation in a welfare program per se” (Moffitt, 1983). This disutility comes from a psychological cost which is due to negative self images because of the participation, or to “negative social attitudes towards welfare claimants” (Besley and Coate, 1992). The first two explanations have been well studied empirically (see Currie, 2006, for a review). But empirical evidence on stigma in social programs take-up is scarce, probably because this channel is hard to measure and identify.

This paper aims at filling this gap, by empirically questioning the role of stigma in welfare take-up in India. The social policy that I am studying is affirmative action in higher education. In India, low castes have a privileged access to universities, thanks to quotas reserved for them. However, they can also choose to not benefit from the quotas, by applying without mentioning their caste. The role of stigma is considered by looking at the impact of households’ social status on their probability of applying for reservations in higher education institutions. Under the hypothesis that stigma increases with social status, which is an hypothesis discussed in section 3, finding that households with a high social status apply less to reservations than households with a low social status is consistent with a stigma effect.
Affirmative action in India is a very interesting case study, because it is applied on a very large scale: almost 50% of the seats for students in higher education institutions are reserved for low castes. However, according to my database, only 15% of the eligible households declare having applied to these quotas in 2005/2006 or 10 years ago. Moreover, the very peculiar social structure of India, the caste system, provides a particularly suitable context to study the impact of stigma on social policies take-up, because castes exogenously determine individuals’ social status.

I focus on a specific group which got eligible for reservations quite recently, the Other Backward Classes (OBC). The OBC category is composed of thousands of subcastes or jatis whose social status varies from one village to the other depending on secular characteristics. As underlined by anthropologists (Dumont, 1970; Srinivas, 1987), one important determinant of the social status of a jati in a given village is the proportion of land that it owns in this village. Therefore, to measure the impact of social status on the probability of applying for reservations in education, I proxy households’ social status by the proportion of land that their jatis own in the village. The distribution of land in villages has the advantage to be historically and exogenously determined as it will be explained in section 3 and consequently to be exogenous to jatis’ characteristics. I also exploit the variation of social status across jatis of a same village and across villages for a same jati to control for unobserved factors at the jati and at the village level.

I find that households from jatis who are socially highly ranked in villages are less prone to apply for reservations than jatis with a lower social status. This effect is stronger for richer households. While there can be other explanations than stigma to this effect, I am able to rule out alternative explanations and notably that the effect just captures different returns to education.

This paper is an important contribution to the literature on welfare take-up. By using exogenous factors related to jatis’ social position, it allows for a clean identification of the impact of social status, and therefore of stigma. In doing so, it provides empirical support to the theoretical literature on stigma (Moffitt, 1983; Besley and Coate, 1992) and confirms previous descriptive results found in the literature, that stigma prevents individuals from benefiting from social programs (Riphahn, 2001; Stuber and Kronebusch, 2004).

It is also an important input to the literature on affirmative action in India.

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1 The ARIS-REDS data.
2 The OBC is a non homogeneous group constituted of many subcastes or jatis. They are higher in the traditional hierarchy than the Untouchables but they are also considered as economically and socially backward. More information is provided in section 2.1.
To my knowledge, it is the first paper to be concerned with the determinants of reservation application. Whereas understanding the determinants of take-up is essential to understand the success or failure of a policy, so far the focus has been solely on the impact of affirmative action programs. Additionally, most of the papers are concerned with reservations in electoral positions (Pande, 2003; Chattopadhyay and Duflo, 2004, see for example). The few papers that focus on affirmative action in education find mixed results. Cassan (2011), using a quasi-natural experiment, finds that affirmative action in education did not have an impact on the education level of scheduled castes. Bertrand et al. (2010), studying labor market outcomes of low castes who benefited from affirmative action to enter universities, find that low castes improve their income by going to the university but less than high castes students.

Finally, this paper brings light into the debate around reservations for OBC. This policy has been accused of favoring the “creamy layers”, that is to say the better-offs, who would not have needed reservations to access universities. The results show that stigma seems to partially compensate this effect by preventing households from powerful castes to apply for reservations.

The rest of the paper is organized as follows. Section 2 describes the Indian context and the reservation policies before focusing on the OBC group and social status. Section 3 explains the empirical strategy and discusses its validity. Section 4 provides details on the data and some descriptive statistics. Section 5 shows the results and section 6 discusses the interpretation of the results. Finally section 7 concludes.

2 Contextual background

Affirmative action in India is caste based. This section therefore briefly describes the caste system and its relation to affirmative action before focusing on the OBC and their status in the Indian society in a second part.

2.1 Affirmative action policies in India

The Indian society is divided in a multitude of castes or jatis. Most jatis are geographically limited and the same jati is rarely present in more than two or three different States, but their scope extends beyond village boundaries. Jatis are hereditary and endogamous groups: one has the same jati as his parents, and has

\[^{3}\text{Hereafter I indistinctly use the words castes or jatis.}\]
to marry within her/his jati. Moreover, jatis have a hierarchical position which is related to their degree of purity, where the degree of purity notably depends on their traditional occupation. Some jatis with intellectual occupations are very pure and are therefore considered as high castes. Other jatis who have very menial jobs are very impure and are considered as low castes. However, the hierarchical position is only clear for jatis at the top and jatis at the very bottom. In between, the classification is more flexible and varies locally. The determination of the position of each jati in the traditional hierarchy is further explained in section 3.1.

The degree of purity and the hierarchical position have important consequences in every day life because they determine how members from different jatis interact with each other. Because of their impurity, people from jatis with a low hierarchical position cannot access certain part of villages or cannot share the food of people from higher jatis. The jati’s hierarchical position is also an important predictor of individuals’ economic status, in part because low castes were restricted to low-skilled occupations but also because they were suffering from discrimination from higher castes, that prevented their economic mobility.

To fight this historically inherited economic and social inequality, affirmative action programs have been put into place in three areas: in elections, in the public sector and in higher education. These affirmative action programs are caste based. One has to be from a jati officially listed to become a beneficiary. Three different categories of jatis have access to affirmative action: the “Scheduled Castes” (SC), the “Scheduled Tribes” (ST) and the “Other Backward Classes” (OBC). The SC, also called Untouchables or dalits are people at the very bottom of the hierarchy. The ST refer to tribal people, and the OBC is a group which is constituted of hierarchically low jatis, but not as low as the SC.

These three groups did not get access to affirmative action at the same time. Whereas the SC and the ST have had reservations since Independence, the OBC got access to reservations progressively, depending on the State. The first States to implement reservations on the same basis as those for SC/ST were the four southern States (Kerala, Karnataka, Andhra Pradesh and Tamil Nadu) (Galanter, 1978) and the last were the States of the Hindu Belt (Rajasthan, Haryana, Uttar Pradesh, Madhya Pradesh). Since 1993, there has also been reservations for OBC in the Central administration\(^4\) and since 2006 in central higher education institutions.

The reason why the OBC got reservations later is because this policy is highly

\(^4\)The word “Central” is used to refer to what is defined at the federal level, and the word “State” to what is defined at the State level.
controversial. The OBC constitute almost 50% of the Indian population.\(^5\) Therefore, extending the quotas to this whole population is not anecdotal and lowers the number of remaining seats for the other castes. It is also a very heterogeneous population in terms of wealth and power. Some OBC had the opportunity to improve their economic status and cannot be considered anymore as disadvantaged. Moreover, among the OBC, some jatis as a whole enjoy locally very influential positions due to their landholding position.

### 2.2 OBC, stigma and social status

As for other social programs, it has been observed that those who benefit from reservations suffer from social stigma. Gudavarthy (2012), who studies the stigmatization of reservations, reports that Scheduled Castes are often referred as *sarkar ke damad* (sons in law of the government). They are also accused to be less competent and the students who got access thanks to reservations in the universities are ostracized by high caste students.

While those at the bottom of the social hierarchy may not care about stigma because they have nothing to lose in terms of social status, the cost of stigma for those with a higher social status is more important. This is especially the case in a country like India where social status has a value in itself (Bloch et al., 2004). Behaviors meant to improve or signal social status have frequently been observed in diverse situations: in eating habits (Srinivas, 1956), in wedding expenditures (Bloch et al., 2004) or in the time allocation of women (Eswaran et al., 2013).

Stigma and social status are two sides of the same coin because the cost of stigma is to lower one’s social status. In this paper, my hypothesis is therefore that the cost of adopting a stigmatized behavior like applying to reservations increases with social status. The rationale is that people with a low social status have little to lose in terms of reputation, whereas people with a high social status suffer much more from a loss in how others consider them. Under this hypothesis, we expect that other things being equal, if there is stigma, people with a higher social status will be less prone to apply for reservations.

My analysis of the impact of social status focuses on the OBC. SC and ST are so low in the traditional hierarchy that we do not expect stigma to prevent them from applying for reservations. On the contrary, OBC, because of their intermediary position in the traditional hierarchy have more room for status improvement.

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\(^5\)This estimation comes from the Mandal Commission, which was established in 1979 with the mission of making a report on the status of the OBC. However, this number is controversial, because it has been calculated with figures from the 1931 census, the last census with details by jatis.
And in fact, according to the literature, OBC attach more importance to status than other groups. Khamis et al. (2012) for example find that OBC spend 8 percent more on visible consumption than high caste groups, after controlling for income. The next section explains how social status is measured.

3 Identification strategy

To measure stigma, I look at the impact of social status on application to affirmative action in higher education. This section explains my measure of social status before turning to the empirical specification *per se* and the identifying assumptions.

3.1 How to measure social status?

3.1.1 Land as a determinant of social status

As explained in section 2, jatis have a hierarchical position which determines the social status of their members. The hierarchy is clear at the broad level: high castes have a higher social status than OBC who have a higher social status than SC and ST. However, the hierarchical position of a given jati within these broad categories is not as clear. In fact, the relative position of a specific jati in comparison to another jati can vary locally.

Anthropologists have underlined that this variation of status within broad groups is largely governed by patterns of land ownership in villages. Srinivas (1987) for example explains that the life of Indian villages is governed by the jati which is economically the most powerful in the village, in other words the jati which owns the most land. This caste is called the “dominant caste”. Dumont (1970), also underlines the importance of land control for dominance.

Following this anthropological literature, I use jatis’ land ownership as a measure of jatis’ local social status. More precisely, households’ social status is measured by the proportion of land owned by their jati in the village. Two things are important to note. First, it is the proportion and not the mean land owned which is used, because jatis do not get power in a village through how much each member in the village possesses, but by how much the jati as an entity possesses. Second, the hierarchical position of a jati is therefore also correlated to how numerous the number of jati members in the village, as underlined by Dumont (1970). However, the proportion of land is preferred over the size of the jati to measure social status, because it is a closer proxy for extreme situations. For example, a very numerous jati without land will have a low social status, whereas members from a jati which has few representatives in the village but possesses the majority of land in the village will enjoy a relatively high social status.
measuring social status through the proportion of land owned by the jati is a proxy. They are other determinants of social status than land in villages. However, in section 6 I provide further empirical evidence that the proportion of land owned by the jati is a good measure of social status. Jati’s land ownership has also already been used in the economic literature to measure power relations in villages (Anderson, 2011).

3.1.2 Exogeneity of land settlement

In addition of really reflecting power relations in the village, for the proportion of land to be a good proxy of jatis’ social status, it also needs to be exogenous to jatis’ characteristics. If some jatis have more land than others because they have different characteristics, land may also proxy for these characteristics. Two main evidence support the exogeneity of land ownership pattern.

First, land ownership in villages is historically determined and has barely changed since the land reforms which took place after Independence. This fact has been documented at the State level by Besley and Burgess (2000) and at the village level by Anderson (2011). Anderson (2011)’s work focuses on Northern India, but the ARIS-REDS data that I am using here show a similar pattern for Southern States. Households’ heads in the 2006 round had been asked about land transactions in their household since they became heads. In total, less than 1.6 % of the households declare having sold or gifted some land during this period. Furthermore, among those who did, 33% transferred the land to family members of friends. Given that most of the relationships are intra-jati, we can globally interpret this as a transfer to persons from the same jati. Therefore, if landownership has been modified, it is only marginally, given that transfers are few in quantity and are mainly to other members of the same jati.

Second, land ownership patterns could also have been modified because of migration. If migration is high and does not affect jatis evenly, it can create endogeneity issues. But migration in rural India is very low. According to the Indian census of 2001, only 4.7% of the total population of India was born outside of the State of residence. This point has been notably studied by Munshi and Rosenzweig (2009) who argue that this is due to strong insurance mechanisms in jatis. Moreover, 43.8% of total migration is migration for marriage purposes. Women migrate to live in their husbands’ family and do not inherit from the land. Consequently, migration did not dramatically affect land distribution across jatis in villages.

7Census of India 2001.
3.1.3 Variation of land ownership pattern

Finally, using the proportion of land as a measure of social status requires that there is variation in the land ownership pattern across jatis and across villages. To show that this is the case, table 3.1 takes the example of the jati composition of two villages situated in the State of Chhatisgarh. Village 1 has seven OBC jatis and village 2 has six. In both villages, there is variation of land ownership between OBC jatis of the same village: in village 1, two jatis own respectively 21% of the land and 47% of the land while the five remaining jatis own each less than 5%. In village 2, the situation is a little more even between the jatis: one jati owns 37% of the land in the village and the other jatis own between 0 and 12% of the land. There is also variation for a same jati across villages: while in village 1 the Kewat own 21% of the land, in village 2 they only have 6% and are among the jatis who have the least land. On the contrary, the Teli who have only 1% of the land in village 1 have 37% of the land in village 2.

The land distribution of these two villages is representative of the situation in the other villages of my sample. This is this variation in land ownership that I exploit to identify the impact of social status on the probability of applying for reservations, as I explain in the next section.

### Table 3.1: OBC jati composition

<table>
<thead>
<tr>
<th>Jati</th>
<th>Village 1</th>
<th>Village 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ahir</td>
<td>0.02</td>
<td>0.12</td>
</tr>
<tr>
<td>Kallar</td>
<td>0.03</td>
<td></td>
</tr>
<tr>
<td><strong>Kewat</strong></td>
<td><strong>0.21</strong></td>
<td><strong>0.06</strong></td>
</tr>
<tr>
<td>Kurmi</td>
<td>0.47</td>
<td>0.08</td>
</tr>
<tr>
<td>Lohar</td>
<td>0.05</td>
<td>0.01</td>
</tr>
<tr>
<td>Nai</td>
<td>0.01</td>
<td>0.02</td>
</tr>
<tr>
<td>Parit</td>
<td>0.03</td>
<td></td>
</tr>
<tr>
<td>Patwa</td>
<td></td>
<td>0</td>
</tr>
<tr>
<td><strong>Teli</strong></td>
<td><strong>0.01</strong></td>
<td><strong>0.37</strong></td>
</tr>
</tbody>
</table>

The two villages are in the State of Chhatisgarh. The total amount of land is not equal to 100% because only the OBC jatis are reported.

3.2 Empirical specification

The role of stigma is studied by estimating the impact of jatis’ social status on households’ probability of applying for reservations, where jatis’ social status is...
measured by the proportion of land owned by jatis in villages. The probability of applying for reservations is measured at the household level, because the data provide the information for this level of aggregation. The empirical specification is as follows:

\[ y_{ijv} = \alpha + \beta LAND_{jv} + \gamma X_{ijv} + \sigma_v + \theta_j + u_{ijv} \]  

where \( y \) is equal to one if a member (including the head) of household \( i \) of jati \( j \) in village \( v \) applied for reservation and zero otherwise. \( LAND_{jv} \) is the proportion of land owned by the jati in the village and \( X_{ijv} \) is a vector of households characteristics.

Unobservables are controlled for at two levels. First, I use the variation of status across OBC jatis in a same village to control for village level unobservables, by adding villages dummies \( \sigma_v \). This accounts for characteristics which are common to all members of the same village, such as access to primary and secondary education, job opportunities or land fractionalization. Second, if the status of a given jati is due to its unobservable characteristics, the measured effect of social status on reservation application is most likely to be biased. To account for that I exploit the fact that there is also exogenous variation of status in a same jati across villages, and I control for jatis unobservables represented by \( \theta_j \) in some specifications.

The equation is estimated with OLS. Although it poses restrictions on the functional form of the relation between social status and application for reservations, with this estimator village and jati dummies can be added at the same time. Robustness checks are provided using conditional logit when jati dummies are not included, but the number of observations per jati is too small to include jati dummies with a logit estimator. The error term \( u_{ijv} \) is clustered at the jati in the village level. Given that the proportion of land owned by the jati measures its local social status, if there is stigma we expect that the probability of applying for reservations decreases with the proportion of land owned by the jati in the village.

4 Data and descriptive statistics

4.1 Data

The data used to conduct this study are from the 2006 round of the ARIS-REDS database from the National Council of Applied Economic Research (NCAER). Since 1971, the NCAER has been conducting household surveys along with village surveys in 259 villages in the 17 major States of India.

The 2006 round is a very peculiar one. Along with the usual questions asked to
a sample of households, a complete census of all the households in every village has been conducted. This is this census that I am using here, because it provides a complete picture of villages social stratification. In particular, households were asked the name of their jati, so I am able to construct the subcaste group of each household.

Households were also asked about their application to reservations in the current year of the survey and 10 years ago. I use this information to construct my dependent variable: it is a dummy variable equal to one if a member of the household applied to reservations in education in 2006 and/or 10 years ago and 0 otherwise.

The variable of interest is the proportion of land owned by the jati in the village. To compute this variable I aggregate by jati the data on households’ land ownership ten years ago. Finally, the census also provides households’ demographic characteristics, that I am using as control variables. In particular, I control for the age of the household’s head, his/her gender, his/her education level, the number of members in the household, and the amount of land owned by the household in log.8

4.2 Sample

My dependent variable relies on information on reservation application ten years ago and in 2006. I therefore concentrate on the States who had reservations for OBC more than 10 years ago. In particular, I exclude Uttar Pradesh, West Bengal, Orissa, Madhya Pradesh, Rajasthan and Haryana because they adopted OBC reservations too recently, as explained in section 2. I also exclude Punjab, because the policy in favor of the OBC is very marginal: the quotas for OBC is only of 5 %, and Himachal Pradesh because there are not enough observations.9 My study consequently focuses on the 9 States represented in figure A3.1 in the appendix. They are almost all in South India.

The identification strategy also requires that there is enough variation in each village in the variable of interest, the proportion of land owned by the jati. I therefore focus on villages where there are at least 3 OBC jatis. The final sample is composed of 28998 OBC households distributed in 92 villages. When jati dummies are included, I also need variation in the variable of interest within jatis. In those specifications, I only include jatis which are present in at least three villages.

8The logarithm transformation is used to take into account the fact that the land variable is very skewed to the left. As several households do not have land this variable is transformed after having added one to the actual value.

9There are only 5 OBC households in Himachal Pradesh in the data.
4.3 Descriptive Statistics

Table 4.2 shows summary statistics separately for the OBC households who applied to reservation and for those who did not.

<table>
<thead>
<tr>
<th></th>
<th>No Application</th>
<th>Application</th>
<th>Diff</th>
<th>Sign</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>46.12</td>
<td>47.27</td>
<td>-1.14</td>
<td>***</td>
</tr>
<tr>
<td>Female</td>
<td>0.11</td>
<td>0.10</td>
<td>0.01</td>
<td>**</td>
</tr>
<tr>
<td>Education</td>
<td>4.44</td>
<td>6.67</td>
<td>-2.23</td>
<td>***</td>
</tr>
<tr>
<td>Size of the HH</td>
<td>4.86</td>
<td>4.92</td>
<td>-0.61</td>
<td>N.S.</td>
</tr>
<tr>
<td>HH Land owned</td>
<td>1.09</td>
<td>1.45</td>
<td>-0.36</td>
<td>*</td>
</tr>
<tr>
<td>Jati prop land</td>
<td>0.28</td>
<td>0.29</td>
<td>0.01</td>
<td>*</td>
</tr>
<tr>
<td>N</td>
<td>24085</td>
<td>4913</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Land owned by the household is in acres.

As we can see, there is selection in application. Households who apply for reservation are more educated (in mean the head of the household has 2.2 more years of education), and they are richer. Given that reservations are supposed to help the most disadvantaged households, this result can seem surprising. However it is in line with the literature (Bertrand et al., 2010) and with the debate on the “creamy layers” explained in the introduction. The proportion of land owned by the jati in the village does not seem to differ strongly depending on the application status.

But if we only look at jatis with a high status in at least one village, the picture is different. Figure 3.1 shows the application rate to reservations in education among jatis which own the highest proportion of land (or dominant jatis) in at least one village.

The left bar represents the application rate of dominant jatis in villages where they are not dominant and the right one in villages where they are dominant. When the jati is dominant in the village, the application rate of households belonging to this jati is lower than when the same jati is not dominant. So it seems that there is a difference of behavior among people in the same jati, depending on the social position of the jati in the village.
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Figure 3.1: Application rate of jatis which are dominant in at least one village

Note: this graph is constructed with OBC jatis that are dominant in at least one village and that are represented in at least in 3 villages. The number of households in this sample is 14027, where 4819 are in villages where the jati is not dominant, and 9208 where the jati is dominant. The difference between the application rate of the two groups is statistically significant from 0 at a 1% level.

5 Results: the determinants of reservation application

5.1 Main results

Table 3.3 shows the results of the estimation of equation 3.1. In columns (1) and (2) the equation is only estimated with controls at the household level. Column (3) to (6) show the results with the proportion of land owned by the jati.

The results on the households characteristics are as expected. Column (1) shows the estimation with village dummies and column (2) shows the estimation with village and jati dummies. The probability of applying for reservations significantly increases with the age of the household’s head, the size of the household, the number of years of schooling of the household’s head and the amount of land owned by the household. All the results are robust to the inclusion of jati dummies and the coefficients are stable, so jati unobservables do not seem to create endogeneity problems. Having a female at the head of the household on the contrary does not matter. Whereas the age of the household’s head and the household size mechanically increase the probability to apply for reservations because the dependent variable is at the household level,\(^{10}\) the results on the edu-

---

\(^{10}\)The age of the household’s head has a positive impact probably because it is positively correlated with the probability that the household has members in age of applying for reservations.
### Table 3.3: Main results: households characteristics and stigma in reservation application

<table>
<thead>
<tr>
<th>Dependant Variable:</th>
<th>Application status to reservation in education</th>
</tr>
</thead>
<tbody>
<tr>
<td>Estimator:</td>
<td>(1) OLS (2) OLS (3) OLS (4) OLS (5) OLS Logit</td>
</tr>
<tr>
<td>Age (Years)</td>
<td>0.000729*** (0.000250) 0.000924*** (0.000283) 0.000748*** (0.000250) 0.000936*** (0.000283) 0.000936*** (0.0139) 0.00737 (0.000285)</td>
</tr>
<tr>
<td>Female</td>
<td>0.00536 (0.00655) 0.00494 (0.00719) 0.00536 (0.00658) 0.00512 (0.00721) 0.00490 (0.00722) 0.0696 (0.132)</td>
</tr>
<tr>
<td>Number of years of schooling &amp; college</td>
<td>0.0107*** (0.00161) 0.0114*** (0.00225) 0.0107*** (0.00186) 0.0114*** (0.00226) 0.0114*** (0.00228) 0.107*** (0.0309)</td>
</tr>
<tr>
<td>Household Size</td>
<td>0.00658*** (0.00161) 0.00685*** (0.00225) 0.00657*** (0.00186) 0.00686*** (0.00226) 0.00685*** (0.00228) 0.0683*** (0.0348)</td>
</tr>
<tr>
<td>HH land owned (in log)</td>
<td>0.00722 (0.00453) 0.00807 (0.00504) 0.00930** (0.00449) 0.00887* (0.00507) 0.00880* (0.00507) 0.0575 (0.0647)</td>
</tr>
<tr>
<td>Jati prop land owned</td>
<td>-0.0455** (0.0188) -0.0544** (0.0256) -0.0555** (0.0258) -0.442 (0.261)</td>
</tr>
<tr>
<td>Jati mean education</td>
<td>0.00190 (0.00397)</td>
</tr>
<tr>
<td>Village dummies</td>
<td>yes yes yes yes yes yes</td>
</tr>
<tr>
<td>Jati dummies</td>
<td>no yes no yes yes no</td>
</tr>
<tr>
<td>Jati control variables</td>
<td>no no no no yes no</td>
</tr>
<tr>
<td>N</td>
<td>28998 23102 28998 23102 23102 26286</td>
</tr>
<tr>
<td>r2</td>
<td>0.319 0.338 0.320 0.338 0.338 0.338</td>
</tr>
</tbody>
</table>

*p < 0.10, **p < 0.05, ***p < 0.01. Standard errors are corrected for clustering at the jati in the village level. Age, female and education are those of the household head. The jati level variables are the mean values of age, female, education and household size calculated over households from the same jati in the village. The concerned household is excluded from the mean calculation.

Column (3) to (6) study the social effects in reservation application by looking at the impact of the proportion of land owned by the jati on the probability of applying for reservations. Column (3) and (4) show the basic estimation of equation (1), without and with jati dummies. In both specifications, the coefficient on the proportion of land owned by the jati in the village is negative and significantly different from zero at a 5% level. In column (3), the estimation is made only with village dummies, showing that the relative social position of the jati within the village has a strong impact on the probability of applying to reservations. The higher is the jati in the village hierarchy, the less are households from this jati significantly more educated and are richer than those who do not apply.
prone to apply. Column (4) shows the results with both village dummies and jati dummies. The coefficient is slightly bigger in absolute value. It confirms that the impact of the jati level variable measured in column (3) is not driven by jati unobservables. Households from the same jati, but in different villages do not have the same probability of applying for reservations: ceteris paribus, households whose jati has more land in one village have a lower probability of applying for reservations in this village than in a village where this jati owns less land. Column (5) includes the control variables at the jati in the village level, to see if the proportion of land owned by the jati does not capture the effect of other jati’s characteristics. I only report the coefficient for jatis’ mean education level, but none of the control variables at the jati level is significant. The coefficient on the proportion of land owned by the jati is still negative and significantly different from zero. Finally column (6) tests the robustness of the results by using a conditional logit to estimate the impact. The result is consistent with what was previously obtained.

The results obtained in column (3) to (6) confirm that the proportion of land owned by the jati in the village has a negative impact on the probability of households from that jati to apply for reservations. As the proportion of land owned by the jati measures social status, under the hypothesis that stigma increases with social status this result is consistent with a stigma effect. However, it is also possible that the demand for education changes with the proportion of land owned by the jati. If this is the case, the same results can be obtained without any stigma effect. This alternative explanation is considered in the next section.

5.2 Alternative explanation: different returns to education

The results previously obtained are consistent with a stigma effect, but there is another valid alternative explanation: it can also be that people who are from a jati which possesses a high proportion of land in the village have lower returns to education. In this case, people from jatis with a high proportion of land apply less to reservations because they do not want to go to the university, and not because of stigma.

This alternative explanation of different returns to education is partially addressed by the fact that the amount of land owned by the household is already controlled for. If differences in land ownership were leading to different returns in education, then controlling for households’ land should have captured the impact of the proportion of land owned by the jati. However, it can still be that the proportion of land owned by the jati captures outside opportunities. For example, households from jatis with a lot of land do not need to go to the university.
to get a job, because even poor households will be able to work on the land of other households from the jati. This section aims at ruling out this alternative explanation, using several robustness checks. The results are shown in table 3.4. I only report the estimations with village and jatis dummies, but they are similar to the ones with only village dummies.

### Table 3.4: Robustness checks

<table>
<thead>
<tr>
<th>Dependant Variable:</th>
<th>Application status to reservation in education</th>
<th>HH’s head educ</th>
</tr>
</thead>
<tbody>
<tr>
<td>Group considered:</td>
<td>(1) OBC</td>
<td>(2) OBC SC/ST</td>
</tr>
<tr>
<td>HH land owned (log)</td>
<td>0.00641 (0.00592)</td>
<td>0.00924 (0.00646)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.0314*** (0.0123)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.738*** (0.0844)</td>
</tr>
<tr>
<td>Jati prop land owned</td>
<td>-0.0517** (0.0257)</td>
<td>-0.0633* (0.0363)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.119 (0.0950)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.325 (0.277)</td>
</tr>
<tr>
<td>Village dummies</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Jati dummies</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>HH control variables</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Jati control variables</td>
<td>no</td>
<td>no</td>
</tr>
<tr>
<td>Occupation</td>
<td>yes</td>
<td>no</td>
</tr>
<tr>
<td>N</td>
<td>23080</td>
<td>12213</td>
</tr>
<tr>
<td>r2</td>
<td>0.346</td>
<td>0.358</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.382</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.284</td>
</tr>
</tbody>
</table>

In column (1), I control for the primary occupation of the household’s head. Given that the returns to education are highly correlated to the occupation that the household has, controlling for this variable should lower the impact of the jati’s proportion of land owned if it captures different returns to education. It is not the case, adding the occupation does not change the impact of the proportion of land owned by the jati.

Column (2) checks if focusing on households whose members have a high probability to get education changes the results. The probability to get education is highly correlated to the education level of one’s parents. So in column (2) I restrict the sample to households whose members have a high probability to get education, that is to say households where the household head is educated. There are not enough households where the household’s head has a university degree so I focus on households whose head has at least finished primary school. In this restricted sample, the impact of the proportion of land owned by the jati is less precisely estimated, but still significant at a 10% level and the coefficient is broadly the same as in the main estimation.

In column (3) I look at the impact of the proportion of land owned by the jati...
CHAPTER 3. STIGMA IN AFFIRMATIVE ACTION APPLICATION?

on the Scheduled Castes and Scheduled Tribes’ (SC/ST) probability of applying for reservations. As explained in section 2, SC/ST have a very low social status, so the stigma attached to reservations should not affect their application. If the negative impact of the proportion of land owned by the jati is due to stigma, then when considering SC/ST the impact should not be negative anymore. But if the proportion of land owned by the jati actually captures different returns to education, then the proportion of land owned by the jati should be negative for both OBC and SC/ST. The result in column (3) contradicts the interpretation of previous findings as driven by different returns to education: for SC/ST the impact of the proportion of land owned by the jati is positive (but not significant).

Column (4) looks at the correlation between the household’s head level of education and the proportion of land owned by the jati in the village. If returns to education diminish with the proportion of land owned by the jati, then we would expect that households’ head from jatis with a high proportion of land have a lower level of education. The results from column (4) contradict this hypothesis: the level of education of households’ heads is not correlated with the proportion of land owned by the jati.

All these robustness checks contradict the interpretation of the main results as a lower return to education for households from jatis with a high proportion of land in the village.

5.3 Heterogeneity of the impact

I now look at the heterogeneity of the impact. Is the impact of social status uniform among households or does it differ depending on households demographic characteristics? I consider two sources of heterogeneity. First, the impact of social status can depend on the education level of the household’s head. One can think for example that more educated people care less about their social status. Second, the impact of social status can depend on the wealth of the household itself. To consider these two questions, I interact the proportion of land owned by the jati with the education level of the household’s head on one hand, and with the amount of land owned by the household (in log) on the other hand. Table 3.5 shows the results of including these interaction terms in the main specification.

Column (1) and column (2) show the results when the education level of the household’s head is interacted with the proportion of land owned by the jati in the village. Column (1) shows the results without jati dummies and column (2) with jati dummies. The interaction term is significant in the first specification but

\[\text{Under the hypothesis the gap between returns in agriculture and in other sectors has not changed over time.}\]
Table 3.5: Heterogeneity of stigma

<table>
<thead>
<tr>
<th>Dependant Variable:</th>
<th>Application status to reservation in education</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
</tr>
<tr>
<td>Number of years of schooling &amp; college</td>
<td>0.0135***</td>
</tr>
<tr>
<td></td>
<td>(0.00242)</td>
</tr>
<tr>
<td>Educ * prop land jati</td>
<td>-0.0107***</td>
</tr>
<tr>
<td></td>
<td>(0.00499)</td>
</tr>
<tr>
<td>Jati prop land owned</td>
<td>0.0125</td>
</tr>
<tr>
<td></td>
<td>(0.0316)</td>
</tr>
<tr>
<td>HH Land owned (in log)</td>
<td>0.0101***</td>
</tr>
<tr>
<td></td>
<td>(0.00448)</td>
</tr>
<tr>
<td>HH Land owned * prop land jati</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>Village Dummies</td>
<td>yes</td>
</tr>
<tr>
<td>Jati Dummies</td>
<td>no</td>
</tr>
<tr>
<td>HH control variables</td>
<td>yes</td>
</tr>
<tr>
<td>Jati control variables</td>
<td>no</td>
</tr>
<tr>
<td>N</td>
<td>28998</td>
</tr>
<tr>
<td>r2</td>
<td>0.32</td>
</tr>
<tr>
<td>Interact &amp; jati var</td>
<td>0.008</td>
</tr>
<tr>
<td>Interact &amp; HH var</td>
<td>0.000</td>
</tr>
</tbody>
</table>

* p < 0.10, ** p < 0.05, *** p < 0.01. The regressions are estimated with OLS and standard errors are corrected for clustering at the jati in the village level. The two last lines of the table report the p-value for the joint significance of the interaction term and the variable with which jatis’ proportion of land owned is interacted.

is not robust to the inclusion of jati dummies. The impact of social status does not seem to differ across different levels of education.

On the contrary, the results on the interaction of the proportion of land owned by the jati with the area of land owned by the household are very interesting. In both specifications with and without jati dummies, the interaction term is negative and strongly significant. This result shows that the negative impact of the proportion of land owned by the jati increases (in absolute value) with the amount of land owned by the household. More clearly, this result shows that the impact of social status is stronger for richer households than for poorer households. It also means that the positive impact of the amount of land owned by the household decreases with the proportion of land owned by the jati. The impact even becomes negative when the household is from a jati which owns a large proportion of land in the village. In other words, while rich households of not so powerful jatis are more prone to apply for reservations than poor ones, rich households from powerful jatis are less prone to apply than poor households. Therefore, it seems that
stigma prevents rich households with high status from applying for reservations.

This result is an additional argument against the idea that the negative impact of the proportion of land owned by the jati is driven by different returns to education across jatis and not by stigma. Indeed, if the proportion of land captures a lower demand for education, then we would expect that rich households in powerful jatis are less affected than poor ones. The rationale is that rich households should not be impacted by the proportion of land owned by their jati if it captures outside opportunities because they already have work opportunities in their own household. But rich households (those with more land) are actually more affected by the proportion of land owned by their jati.

6 Discussion

Section 4 underlines strong effects for OBC households of the proportion of land owned by their jati on affirmative action application. These results are robust and do not seem to be driven by village or jati level unobservables. In this section I continue the discussion began in section 5.2 on the interpretation of the results. In the first subsection I provide empirical evidence that the proportion of land owned by the jati really measures jatis’ social status. In the second subsection I discuss another alternative explanation than stigma to the impact, the role of information.

6.1 Ownership of land and political outcomes

The measure of social status through jatis’ land ownership comes from the anthropological literature as explained in subsection 3.1, and has been previously used in the economic literature (Anderson, 2011). However, one can still be doubtful about its relevance in contemporary India. To give empirical credit to this measure, I study the relation between the proportion of land owned by the jati and another outcome to which social status is also strongly related, being a candidate to elections.\(^\text{12}\) Therefore, if the proportion of land owned by a jati actually measures its members’ social position in the local hierarchy, we expect that people from this jati have a higher probability to be candidates\(^\text{13}\) in local elections other things being equal.

\(^{12}\)In India, it has been shown that when elections are not reserved to a specific caste group, local electoral positions are often taken by members from castes who socially dominate village life (Witsoe, 2009; Anderson et al., 2011).

\(^{13}\)Household level informations on election output are not available.
Table 3.6: Political outcomes

<table>
<thead>
<tr>
<th>Dependant Variable:</th>
<th>Candidate to a local election</th>
</tr>
</thead>
<tbody>
<tr>
<td>Level of aggregation:</td>
<td>(1) Household</td>
</tr>
<tr>
<td>HH land owned (log)</td>
<td>0.0114***</td>
</tr>
<tr>
<td>Jati prop land owned</td>
<td>0.0151***</td>
</tr>
<tr>
<td>Village Dummies</td>
<td>yes</td>
</tr>
<tr>
<td>Jati Dummies</td>
<td>no</td>
</tr>
<tr>
<td>HH control variables</td>
<td>yes</td>
</tr>
<tr>
<td>Jati control variables</td>
<td>no</td>
</tr>
<tr>
<td>N</td>
<td>28998</td>
</tr>
<tr>
<td>r²</td>
<td>0.0451</td>
</tr>
</tbody>
</table>

* p < 0.10, ** p < 0.05, *** p < 0.01. The regressions are estimated with OLS. Standard errors are corrected for clustering at the jati in the village level for columns (1) and (2) and at the village level for columns (3) and (4).

The equation estimated is the same as before, except that the dependent variable is now \( candidate_{ijv} \):

\[
candidate_{ijv} = \alpha + \beta LAND_{jv} + \gamma X_{ijv} + \theta_j + \sigma_v + u_{ijv} \quad (3.2)
\]

where \( candidate_{ijv} \) is equal to one if someone of the household has been a candidate to any local election (panchayat and pradhan) and zero otherwise.

In column 1, the equation is estimated with village dummies and in column 2 with village and jati dummies. In both specifications, the amount of land owned by the jati is positive, showing that being from a jati which owns a lot of land in the village increases the probability of being a candidate.

However, given that the proportion of land owned by the jati is also positively correlated to how numerous the jati is, it is not surprising that being from jatis with a high proportion of land increases the probability of being a candidate. To check if this is the size of the jati that is driving the impact, I run the same regressions but at the jati level. The dependent variable is now the proportion of households who are candidates to local elections per jati. Column (3) shows the estimation with village dummies. The results confirm what was obtained at the household level. In column (4) with jati dummies the coefficient is not as precisely estimated but has the same size and sign as before.

These results underline that the proportion of land owned by the jati seems to be a good measure of social status.
6.2 Additional alternative explanation: the information channel

I shall now discuss the interpretation of the negative impact of the proportion of land owned by the jati as a stigma effect. One alternative explanation, the different returns to education across jatis, has already been considered in section 5.2. Here I look at another alternative explanation besides stigma: the fact that the effect can capture other costs to reservation application than stigma.

The theoretical literature underlines other possible social effects than stigma in welfare take-up (Moffitt, 1983). In particular, information has been shown to be an important determinant of program participation (Aizer, 2007; Heckman and Smith, 2004). Information sharing is consequently another channel through which the group could affect reservation application. One could argue that the measured social effect actually captures this information channel. However, several facts contradict this argument.

First, we would expect households from more powerful jatis - jatis with a higher proportion of land- to be better informed. So if the proportion of land owned by the jati captures information effects, we would expect that being in a jati which owns a high proportion of land would have a positive impact on the probability of applying for reservations.

Second, it has been shown that in India, higher educated people have better access to information (Foster and Rosenzweig, 1996). Therefore, if there are social effects related to information sharing, we expect that the mean education level of neighbors has an impact on the probability of applying for reservations, or that the impact of social status diminishes with the education level of the household’s head. In column (5) of table 3.3 jatis’ mean education level is not significant and its inclusion does not affect the coefficient of the proportion of land owned by the jati. Moreover, columns (1) and (2) of table 3.5 does not show any decrease of the impact with the households’ head education level. Consequently, the results that I obtain do not seem to be driven by an information effect.

7 Conclusion

Determining who among the ones who have the right to benefit from welfare programs actually take advantage of them is very important for policy designs. In this paper, I am concerned with a very controversial program, an affirmative action program in favor of disadvantaged castes in India in higher education. This program is addressed to the “Other Backward Classes”, an heterogeneous entity composed of groups with very different social and economic status. Given that the jatis (subcaste groups) concerned by this program are hierarchically higher in the
CHAPTER 3. STIGMA IN AFFIRMATIVE ACTION APPLICATION?

traditional ranking of castes than the groups historically targeted for affirmative action (the untouchables), stigma may actually have a role in the choice of applying to reservations.

To study that, I look at the impact of households social status on their probability of applying for reservations. I find that being from a locally powerful caste has a negative impact on reservation application. I also find that this impact is stronger for households with more land. These results are not driven by village or jati unobservables and do not capture different returns to education across jatis. It therefore seems that stigma may be at stake in keeping households from locally high subcastes to apply for reservation.

This paper consequently shows that part of the low-take up that we observe in welfare programs may be due to stigma. But although stigma may have dramatic effects when it affects the take-up of health-related programs, in this specific context the consequences do not seem as tragic. Indeed, the take-up of the lowest castes, the SC/ST, is not affected. Moreover, among the OBC, it only affects the richest households from the most powerful jatis. In quotas in higher education, stigma therefore seems to play the role of control barriers to prevent the better-offs from applying to programs that are not designed for them. However, it is important to keep in mind that even if stigma only reduces the take-up rate of the highest castes, stigma may still affect the well-being of those who choose to benefit from it, and as such needs to be taken into account by policy makers. Further research is needed to clarify this issue.
CHAPTER 4

How to get a job in the public sector? The role of local politics and caste networks in affirmative action programs in India
1 Introduction

Past discrimination against certain people on the basis of their ethnicity, religion or gender has had an important impact on current inequalities. Because those groups were restricted to certain occupations or deprived from certain rights, today, they are lagging behind their country counterparts in terms of socio-economic outcomes. This is for example the case for the African Americans in the US, the Malay in Malaysia, the indigenous population in Brazil or women all over the world. To make up for this situation, a lot of countries have set up affirmative action programs in favor of those groups.

In India, where certain individuals were discriminated against because of their caste, affirmative action programs are implemented on a very large scale. The extent of affirmative action is particularly spectacular in public employment where since Independence, depending on the State, between 22.5% and 49.5% of the jobs in the public sector have been reserved for low castes. However, each year a non-marginal proportion of these quotas remain unfilled and low castes are still underrepresented in the public sector. Two main reasons can explain this failure in filling the quotas. The first reason is that although there are candidates, they are not considered as “suitable” (Jaffrelot, 2011). It can be sometimes true, but it is often used as an excuse by recruiters that do not want to hire low castes, because after several unsuccessful recruitments the position is opened up to all castes. The second reason, which is the one in which this paper is interested in, is that it is not easy to access these jobs, because the recruitment is highly discretionary. Chandra (2004) reports that except for high skilled positions which are filled by competitive exams, a high proportion of the employees at low skilled positions, which constitute almost 95% of the jobs in the public sector, are recruited directly by the offices concerned. This discretion in hiring makes it difficult for low castes individuals without connections to access these jobs and therefore benefit from reservations in the public sector. Chandra (2004) describes the case of an untouchable in a village in Uttar Pradesh, who is eligible for quotas in public sector employment but does not even try to benefit from them because “had he tried to escape his circumstances by securing regular employment in the public sector, he would have needed “contacts””. This difficulty in getting benefits from the State without connections not only concerns reservations in public employment, but a large range of public programs. Therefore, intermediaries are commonly used to mediate people’s access to State institutions (Witsoe, 2012). Among these intermediaries, political leaders, who have power over administrative decisions,
play an important role.

The question I am concerned with in this paper is if households that are better connected to the State through their caste networks have an easier access to reserved jobs in the public sector. Because I do not know if households got the job after applying, I study the impact of caste networks on application for reserved jobs. More concretely, I look at the impact of having someone from the same caste as a local elected leader on the probability of applying for reservations in the public sector. What is the mechanism? Elected leaders in India do not concretely have the power to attribute administrative jobs. However, they have a certain control over bureaucrats, because they can transfer them across different posts (Chandra, 2004; Iyer and Mani, 2012). The impact that I am looking at is therefore indirect: local leaders, because of their connections, play the role of intermediaries between their caste members and the bureaucrats.

As the caste group of elected leaders is not random, I exploit the institutional reform of 1993 in India that has created a three-tier government system, with elected councils at the village, block and district levels. In addition of giving more power over expenditures to village councils (also called Gram Panchayats), this reform established that the position of village council president (alternatively called “pradhan”) had to be reserved for low castes in a certain number of villages, where the number of villages in each State is determined by the proportion that low castes represent in their State population. I use the fact that reservations for the position of president in village councils determine the caste group of the person in power, to look at the impact of having someone from the same caste group as a pradhan on the probability of applying for reservations in the public sector. To take into account the fact that the attribution of political reservations to a specific caste group in a specific village is partially determined by village level characteristics, I focus on intra-village variation across caste groups in the probability of applying for reservations in public employment.

I first document that sharing the same caste group as the pradhan increases households’ application for reservations in the public sector. Secondly, I show that this impact is actually restricted to members from the same subcaste (also called jati). There are competitive explanations for this impact, but evidence suggests that this is due to the pradhan actually helping the application of members from his caste group to be processed. The other channels such as an improved self-confidence or a better access to information are not supported by several results

2 Whereas every village get political reservations for each caste group at some point in time, the sequence in which villages get political reservations is not random, therefore leading to systematic differences across villages in their observable characteristics (Dunning and Nilekani, 2013). This point will be further explained in section 4.1.
provided in the paper.

The fact that elected political leaders favor their own group in the distribution of benefits has been well documented in the literature. Looking at the impact of electoral reservations for scheduled castes (SC) and scheduled tribes (ST) at the State level in India, Pande (2003) finds that they have increased redistribution of resources in favor of these groups. The same pattern has been observed at a more local level. Besley et al. (2004) show that the intra-village allocation of public goods is shifted towards low castes when the seat of the pradhan is reserved for low castes. Similarly, Chattopadhyay and Duflo (2004) find that female pradhans distribute public goods which are more relevant to the needs of women.

There is less empirical evidence in the economics literature on how having someone from their group in power changes the behavior of individuals, because they expect different returns from their actions, or because they feel more confident to do so. Among the exceptions, Beaman et al. (2009) find that female reservations for the seat of pradhan leads to an increase in the proportion of female candidates in successive elections.

This paper provides new empirical evidence that emphasizes the importance of caste networks in getting access to State benefits. Whereas previous literature has mainly focused on the impact of political leaders’ identity on the distribution of public goods, this paper studies a different kind of public benefit, namely quotas for low castes for jobs in the public sector. This policy is the biggest affirmative action program in the world, but little is known about the mechanisms underlying people’s application. This paper therefore sheds some light into what determines or keeps people from taking advantage from reservations in the public sector.

The rest of the paper is organized as follows: section 2 provides some information on the caste system and caste-based affirmative action programs. Section 3 describes the data used and gives some descriptive statistics. Section 4 explains the empirical strategy before showing the main results and exploring the channels. Finally, section 5 concludes.

2 Contextual background

The affirmative action policy in India is due to, and based on, the caste system. To understand the policy studied in this paper, this section provides basic information on the caste system before giving a quick overview on the evolution of reservations in public employment.
2.1 The caste system and the need for reservations

The Indian society is stratified according to a caste system. The organization of the caste system is hierarchical, and is governed by the concept of purity and impurity. People at the top of the hierarchy are considered to be pure, whereas people at the bottom are very impure and therefore “untouchable”. The caste system goes hand in hand with a division of occupations across subcaste groups (or jati), where each subcaste group has a traditional occupation. Low caste groups are traditionally doing menial jobs such as scavenging or clothes cleaning. Membership to a specific subcaste (jati) is hereditary and endogomy is practiced, such that it is very difficult, not to say impossible, to escape one’s caste.

Because the caste system in itself does not allow for social mobility, the caste group at the bottom of the social hierarchy, the untouchables (also called dalits), have always been the most economically disadvantaged group. And because of their impurity, they were and still are suffering from discrimination: they had been obliged for centuries to live in specific areas of villages, they were forbidden from using common goods such as wells or places of worship.

At Independence, under the lead of Dr. Ambedkar himself a dalit, affirmative action was written in the Constitution. The untouchables, named as the “Scheduled Castes” (SC) and the indigenous people of India under the name of “Scheduled Tribes” (ST) were provided with respectively 15% and 7.5% quotas in public employment and in higher education institutions. The other low castes, also economically poor and socially backward but not suffering from the stigma of untouchability, were not benefiting from this policy. But a door was left open for them in the Constitution where they were referred as the “Other Backward Classes” (OBC).

2.2 The evolution of reservations for low castes in public employment

Whereas reservations in public employment for SC and ST were quickly implemented and accepted, reservations in public employment for OBC were subjected to several twists and turns and were extremely diverse across States. There has been reservations in the public sector for OBC in the Southern States prior to Independence. During the post-Independence period, several other States adopted reservations for OBC. However, the turning point was the “Mandal Commission”

3For clarity purposes, in the rest of the paper, when I refer to “caste” it relates to the broad caste group, namely SC, ST and OBC, and when I refer to “jati” it relates to the hereditary and endogamous subcaste groups which compose each caste group.
of 1979 which recommended 27% quotas in the public sector for OBC. This recommendation was implemented by the Central Government in 1993. Most of the States followed the Central Government and implemented reservations for OBC in their own services, the most recent State being West Bengal which only gave reservations in the public sector for Muslim OBC in 2012.

Currently, there are employment quotas in the public sector (central and State Government) for SC, ST and OBC in every State.

3 Data and descriptive statistics

The data used to conduct this study are from the 2006 round of the ARIS-REDS database from the National Council of Applied Economic Research (NCAER). Since 1971, the NCAER has been conducting household surveys along with village surveys in 259 villages in the 17 major States of India.

Out of the 259 villages where the survey has been conducted, I focus on a subsample for which the jati of the pradhan is available. This is the case for 37 villages situated in three States: Andhra Pradesh, Karnataka and Maharashtra. In those villages, I focus on households from castes benefiting from reservations in public employment, namely SC, ST and OBC. The final sample is composed of 14,081 households. Robustness checks on specifications which do not require the jati of the pradhan are conducted with a broader sample including all the States which have political reservations for OBC and reservations for OBC in State government jobs. The additional States in this sample are Chhattisgarh, Gujarat, Rajasthan, Tamil Nadu and Uttar Pradesh.

The village survey provides the reservation status of the president council position for three periods: current pradhan, previous pradhan and previous to previous pradhan. Table 4.1 summarizes the information for the reduced sample, and for the broader sample used for robustness checks. Two important points are to be noted: first, OBC benefit the most from pradhan’s reservation. Each electoral term, more than 50% of the reserved pradhan seats are reserved for OBC. Second, the number of reserved seats constitute almost 50% of the total number of seats.

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4 The data do not directly provide the jati of the pradhan, but indicate the name and several socio-demographic indicators along with their electoral score of all the candidates to the seat of pradhan. We also know for all the village members if they were candidate for the seat of pradhan. The jati of the pradhan can be deduced in two specific institutional contexts: when the pradhan is elected among the Gram Panchayat members as in Maharashtra and Karnataka, because the data indicate the jati of panchayat members, or when the Gram Panchayat is composed of only one village, in which case we can match the pradhan to the listing.

5 Although reservations for SC and ST for the president council position are imposed by the Constitution, reservations for OBC are allowed but not mandatory. Therefore, not all States have implemented political reservations for OBC.
Table 4.1: Villages reservation status

| Pradhan position reserved for | Reduced sample | | | Broad sample | | |
|-------------------------------|----------------|-------------------|----------------|-------------------|-------------------|
|                               | current | previous | previous to previous | current | previous | previous to previous |
|                               | nb | % | nb | % | nb | % | nb | % | nb | % |
| SC                            | 3   | 8%  | 6   | 16% | 8   | 22% | 14  | 10% | 17  | 12% |
| ST                            | 4   | 11% | 1   | 3%  | 4   | 11% | 9   | 6%  | 7   | 5%  |
| OBC                           | 20  | 54% | 18  | 49% | 13  | 35% | 47  | 33% | 40  | 28% |
| Total Reserved                | 27  | 73% | 25  | 68% | 25  | 68% | 70  | 49% | 64  | 45% |
| Non Reserved                  | 10  | 27% | 12  | 32% | 12  | 32% | 73  | 51% | 79  | 55% |
| Total                         | 37  | 100%| 37  | 100%| 37  | 100%| 143 | 100%| 143 | 100%| 128 | 100%|

The table indicates the number of villages where the seat of pradhan is reserved for SC, ST or OBC, in the reduced sample and the broad sample, for current and previous Gram Panchayat.

for the reduced sample and up to 70% for the reduced sample.

The information about application to reservations for jobs in the public sector is provided in the household survey. The 2006 round is a very peculiar one, because along with the usual questions asked to a sample of households, a complete census of all the households in every village has been conducted. Though the number of questions asked is much smaller than to the sample of households, several questions on reservations have been asked to the households, along with their demographic characteristics. Households were asked about their applications to reservations for jobs in the public sector in the current year of the survey and 10 years prior.

Table 4.2 provides descriptive statistics for the most important variables for the reduced sample. The mean application rate to reservations in public employment is rather low and stable over time: 4.6% of the households declare having applied to reservations in 1996 and 4.2% in 2006. Concerning the pradhan, as expected from table 4.1, the proportion of households with a low caste pradhan is very high: 56% of the households in the sample live in a reserved Gram Panchayat. However, only 37% have a pradhan seat reserved for households from their respective caste group. The OBC are the most favored. Among them, 34% of the households benefit from a OBC-reserved pradhan. On the contrary, only 2% of the SC and 2% of the ST have a seat reserved for their caste group.

The demographic characteristics are consistent with what we find in chapter 2 and 3. Low castes are poor and are not very educated. On average their education level is below primary, and they have small landholdings.
4 Results

This section studies if households apply more for reservations in the public sector when they are from the same jati as their pradhan. I first focus on the impact of being from the same caste in subsection 4.1, before looking specifically at the impact of being from the same jati in subsection 4.2. In subsection 4.3 I study what drives the impact measured in the previous subsections.

4.1 Impact of having a pradhan from the same caste

To estimate the impact of having someone from the same caste group as a pradhan on the probability of applying for reservations in government jobs, I take advantage of the reservation system for the position of pradhan. Instead of directly looking at the impact of the caste of the pradhan, which may lead to endogeneity issues, I use the fact that the electoral reservation system imposes that in some villages, only members from a specific caste group can be candidates for the position of pradhan. In the area I am focusing one, the position of Pradhan can be

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6There can be a problem of omitted variables if caste unobservable characteristics, such as connections outside of the village, drive the probability of being elected and of applying for reservations.
reserved for SC, ST or OBC. When it is not reserved, anyone from any caste group can be a candidate. In practice, low castes are rarely elected when the seat is not reserved. In my sample, only two low caste pradhans have been elected without reservations.

The 73rd amendment of the Constitution, which put this policy into place, specifies that “the number of offices of Chairpersons reserved for the Scheduled Castes and Scheduled Tribes in the Panchayats at each level in any State shall bear, as nearly as may be, the same proportion to the total number of such offices in the Panchayats at each level as the population of the Scheduled Castes in the State or of the Scheduled Tribes in the State bears to the total population of the State”.

For OBC, States do not have to provide reservations for the seat of pradhan but, for those who choose to, the number of seats to be reserved is also determined by law. In Karnataka and Andhra Pradesh, 1/3 of the seats for Chairpersons are to be reserved for OBC, and in Maharashtra it is 27%. Concretely, in most States, the proportion of pradhan seats to be reserved for each caste group is determined at the block level (i.e subdistrict) and is approximately equal to the share that they represent in the population of the subdistrict.7

But what matters for identification, is how the reserved seats are attributed to each Gram Panchayat. The 73rd Amendment specifies that the reserved seats have to be allocated by “rotation” across Gram Panchayats, but the order in which each Gram Panchayat get electoral reservation is not specified in the text. In practice, Gram Panchayats are classified according to a specific criterion, which is most of the time the size of the population considered in each Gram Panchayat.8 In Karnataka, for example, for the attribution of reserved seats for SC, Gram Panchayat are listed in a descending order by the size of their SC population. The sub-district bureaucrats go down the list to allocate the reserved seats (Dunning and Nilekani, 2013). The strategy is the same for OBC reservations in Bihar, except that Gram Panchayats are classified in the descending order of their total population, given that the OBC population is not known. So even if every Gram Panchayat get reservations at a certain point in time, the fact that they get reservation at a specific electoral term is not random, because the order of allocation is determined by a village-level criterion. In a cross-sectional setting, villages with reservations are therefore not similar to villages without reservations and the impact of having a pradhan from the same jati cannot be identified.

To overcome this issue, I use the same identification strategy as Besley et al. (2004), who add village dummies to their specification. The village dummies

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7The exact OBC population is not known, because since 1931 the census does not provide figures per caste.
8However, the criteria is not known for all States.
capture all the village-level unobservables which may be correlated to the reservation status of the village and to the rate of application for reservations in the public sector of a specific caste group, such as the size of their caste group. The impact of having a pradhan from the same caste group on job reservation applications is therefore only identified from within village variation in application. The empirical specification is as follows:

\[ Y_{hcv} = \beta_0 + \beta_1 X_{hcv} + \beta_2 CASTE_c + \beta_3 CASTE_c \times R_v + \alpha_v + \epsilon_{hcv} \] (4.1)

where \( Y_{hcv} \) is equal to one if a member from household \( h \) of caste \( c \) (namely SC, ST or OBC) in village \( v \) applied to reservations for jobs in the public sector. \( X_{hcv} \) are household level variables. \( CASTE_c \) indicates the caste identity (SC, ST or OBC) of the household. \( R_v \) is a set of dummy variables equal to one if the position of pradhan in the village is reserved for SC, ST or OBC. The interaction term between \( CASTE_c \) and \( R_v \) is therefore a dummy variable equal to one if the pradhan’s position is reserved for the caste group of the household. The village dummies \( \alpha_v \) control for the unobservables at the village level which may be correlated to the reservation status and \( \epsilon_{hcv} \) is an error term. The standard errors are clustered at the level of the interaction term, that is to say at the caste in the village level.

The probability of getting reservations is correlated to the size of the SC, ST and OBC population in the block. Some other outcomes at the caste level influencing reservation application may also be correlated to the size of these groups. To take that into account, in some specifications, the regression is also estimated with an interaction term between the caste group and district dummies. Once controlling for this, households from each caste group is similar in reserved and unreserved Gram Panchayat (see table A4.1 in the appendix).

In an alternative specification, I use the panel dimension of the data to look at the impact of having someone from the same jati as a pradhan on application to reservations for jobs. In the survey, households were asked about their application to reservations at the time of the survey (2005-2006) and ten years prior (therefore 1995-1996). For most villages, the data also provide the information on reservations for the seat of pradhan 10 years ago. I am therefore able to study the impact in a panel setting with households fixed effects, where the identification comes from villages where there was a change in the reservation status of the

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9Age and education level of the household head, land owned, household size and religion.

10As explained previously, the fact that a village gets reservation for a certain group at a certain point in time depends on its position on the list, which itself depends on the distribution of each caste group in the other villages of the block. The probability of getting reservation consequently depends on the SC, ST and OBC population in the other villages.
pradhan seat. The econometric specification is as follows:

\[ Y_{htcv} = \gamma_0 + \gamma_1 \text{CASTE}_c \ast R_{tv} + T_t + \theta_{tv} + \beta_{hcv} + \xi_{htcv} \]  

where \( R_{tv} \) indicates, as before, if the pradhan’s position is reserved for a specific caste at time \( t \) in village \( v \), \( T_t \) is a time dummy, \( \beta_{hcv} \) is a household fixed effects, which controls for time-invariant unobservables and \( \theta_{tv} \) controls for time-variant village-level unobservables. I do not control for the caste of the household, because it does not vary over time, and it is absorbed by the household fixed effects. Because the data do not have a real panel structure, I am also not able to control for households’ characteristics which vary over time. However, it should not really bias the estimation because the variable of interest is at the caste level. Standard errors are corrected for two-way clustering at the household level and at the level of the interaction term, that is to say at the caste in the village-year level.

4.1.1 Cross-sectional evidence

I first begin by looking at cross-sectional evidence of the impact of having someone from the same caste as a pradhan.

Table 4.3 shows the results of the estimation of equation 1. Column 1 looks at the impact of reservations for SC, ST and OBC, and shows that having a pradhan from the same caste group has a positive impact on the probability of members from this caste group to apply for job reservations. Columns 2, 3 and 4 differentiate between the different caste groups. Column 2 and 3 show that having a pradhan who is a SC (column 2) or a ST (column 3) does not increase the probability of applying for reservations of SC or ST. However, having an OBC pradhan for OBC households has a strong and positive impact on their probability of applying for reservations (column 4). One explanation for the absence of relation between having a SC/ST pradhan and applying to reservations in jobs for SC/ST can be that SC/ST pradhans who are elected when the position is reserved for SC/ST are often said to be “puppet candidates” for high castes. Because high castes cannot officially compete in the elections, they help a SC/ST to win such that they keep control over the council president position. Therefore, the SC/ST candidate elected with the support of high castes does not truly have power over the decisions. OBC on the contrary have more social power than SC/ST and are able to have a candidate not instrumented by high castes. The positive impact for OBC is robust to the addition of caste level controls (column 5) and district

\[ \text{The number of reserved villages for SC or ST in this sample is very small (cf table 4.1), but the same regressions on the broad sample (not shown here) confirm these results.} \]
Table 4.3: OLS estimation of application to reservation for jobs

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dependent Variable: Application to reservations for jobs</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age (Years)</td>
<td>0.000779**</td>
<td>0.000782**</td>
<td>0.000783**</td>
<td>0.000781**</td>
<td>0.000789**</td>
<td>0.000812**</td>
<td>0.000997**</td>
<td>0.00107**</td>
</tr>
<tr>
<td></td>
<td>(0.000207)</td>
<td>(0.000206)</td>
<td>(0.000206)</td>
<td>(0.000207)</td>
<td>(0.000221)</td>
<td>(0.000296)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Years of schooling</td>
<td>0.00343**</td>
<td>0.00344**</td>
<td>0.00344**</td>
<td>0.00343**</td>
<td>0.00350**</td>
<td>0.00333**</td>
<td>0.0104**</td>
<td>0.00498**</td>
</tr>
<tr>
<td></td>
<td>(0.00118)</td>
<td>(0.00118)</td>
<td>(0.00118)</td>
<td>(0.00118)</td>
<td>(0.00119)</td>
<td>(0.00125)</td>
<td></td>
<td>(0.00145)</td>
</tr>
<tr>
<td>Land owned in acres</td>
<td>0.000321</td>
<td>0.000318</td>
<td>-0.0000926</td>
<td>0.00138</td>
<td>0.00162</td>
<td>-0.000423</td>
<td>-0.000622</td>
<td></td>
</tr>
<tr>
<td>(in log)</td>
<td>(0.00257)</td>
<td>(0.00256)</td>
<td>(0.00257)</td>
<td>(0.00258)</td>
<td>(0.00259)</td>
<td>(0.00286)</td>
<td>(0.00339)</td>
<td>(0.00378)</td>
</tr>
<tr>
<td>Household Size</td>
<td>0.000580</td>
<td>0.000552</td>
<td>0.000549</td>
<td>0.000583</td>
<td>0.000619</td>
<td>0.000456</td>
<td>0.0199**</td>
<td>0.00184*</td>
</tr>
<tr>
<td></td>
<td>(0.00116)</td>
<td>(0.00116)</td>
<td>(0.00116)</td>
<td>(0.00116)</td>
<td>(0.00116)</td>
<td>(0.00123)</td>
<td>(0.00309)</td>
<td>(0.00109)</td>
</tr>
<tr>
<td>ST household</td>
<td>-0.0197**</td>
<td>-0.0179*</td>
<td>-0.0166</td>
<td>-0.0195**</td>
<td>-0.0206**</td>
<td>-0.00914</td>
<td>0.0102</td>
<td>0.0268*</td>
</tr>
<tr>
<td></td>
<td>(0.00935)</td>
<td>(0.00989)</td>
<td>(0.0106)</td>
<td>(0.00888)</td>
<td>(0.00829)</td>
<td>(0.0102)</td>
<td>(0.0160)</td>
<td>(0.0207)</td>
</tr>
<tr>
<td>OBC household</td>
<td>-0.0310**</td>
<td>-0.0250**</td>
<td>-0.0250**</td>
<td>-0.0365**</td>
<td>-0.0293**</td>
<td>-0.0364**</td>
<td>-0.0463**</td>
<td>0.0157</td>
</tr>
<tr>
<td></td>
<td>(0.00572)</td>
<td>(0.00655)</td>
<td>(0.00638)</td>
<td>(0.00471)</td>
<td>(0.00529)</td>
<td>(0.0127)</td>
<td>(0.0160)</td>
<td>(0.0207)</td>
</tr>
<tr>
<td>Elect reserv * caste</td>
<td>0.0144*</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00684)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SC reserv * SC</td>
<td>0.000714</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0155)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ST reserv * ST</td>
<td>-0.00983</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0104)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Religion dummies</td>
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<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Village dummies</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Caste level controls</td>
<td>no</td>
<td>no</td>
<td>no</td>
<td>no</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Caste*District dummies</td>
<td>no</td>
<td>no</td>
<td>no</td>
<td>no</td>
<td>no</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>N</td>
<td>14081</td>
<td>14081</td>
<td>14081</td>
<td>14081</td>
<td>14081</td>
<td>13086</td>
<td>48951</td>
<td>13086</td>
</tr>
<tr>
<td>r²</td>
<td>0.0617</td>
<td>0.0614</td>
<td>0.0614</td>
<td>0.0620</td>
<td>0.0631</td>
<td>0.0636</td>
<td>0.158</td>
<td>0.148</td>
</tr>
</tbody>
</table>

*p < 0.10, **p < 0.05, ***p < 0.01. Robust standard errors are corrected for clustering at the caste in the village level. The sample in columns 5 and 7 exclude districts where there is only one village for which data are available, to keep some variation when the interaction terms between caste and district dummies is added. Column 6 is using the extended sample. The caste level controls are the household level controls aggregated at the caste level, i.e. age, education, land owned and household size.
dummies interacted with caste (column 6), so the impact does not seem to be driven by caste unobservables. As this specification does not use the jati of the pradhan, I can test the impact on the bigger sample. Column 7 shows that the result is robust to a sample change. Column 8 confirms the previous results by using a placebo test. If the impact is driven by caste unobservables at the village level which are correlated with having reservations for the seat of pradhan and the probability of applying for reservations, we would expect that the interaction term between reservations for OBC and the OBC dummy is also positively correlated to the probability of applying for reservations 10 years ago. However this is not the case, the coefficient interaction term is close to 0 and is not significant.

Worth noting also is that on average the SC and ST apply more for reservations for administrative jobs. This may be explained by the fact they they got quotas in the public sector much earlier than the OBC.

### 4.1.2 Panel evidence

Table 4.4 provides further evidence of the robustness of the impact for OBC by using the panel specification. Equation 4.2 is estimated using a fixed-effects procedure, where the unit is the household. In this specification, households who have moved into the village after 1993 are excluded.

<table>
<thead>
<tr>
<th>Dependant Variable: Application to reservations for jobs</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2006 year</td>
<td>-0.0160**</td>
<td>-0.0193*</td>
<td>0.0137</td>
<td>0.0118</td>
</tr>
<tr>
<td></td>
<td>(0.00736)</td>
<td>(0.0107)</td>
<td>(0.00884)</td>
<td>(0.00939)</td>
</tr>
<tr>
<td>OBC reserv * OBC</td>
<td>0.0259***</td>
<td>0.0373***</td>
<td>0.0131**</td>
<td>0.0151*</td>
</tr>
<tr>
<td></td>
<td>(0.00743)</td>
<td>(0.0130)</td>
<td>(0.00635)</td>
<td>(0.00787)</td>
</tr>
<tr>
<td>OBC reserv * OBC *</td>
<td>-0.0211</td>
<td>-0.00400</td>
<td>-0.00400</td>
<td>-0.00400</td>
</tr>
<tr>
<td></td>
<td>(0.0216)</td>
<td>(0.0117)</td>
<td>(0.0117)</td>
<td>(0.0117)</td>
</tr>
<tr>
<td>OBC * 2006</td>
<td>0.0150</td>
<td>0.00339</td>
<td>0.00339</td>
<td>0.00339</td>
</tr>
<tr>
<td></td>
<td>(0.0119)</td>
<td>(0.00502)</td>
<td>(0.00502)</td>
<td>(0.00502)</td>
</tr>
<tr>
<td>Village * time dummies</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Households FE</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>N</td>
<td>13553</td>
<td>13553</td>
<td>43594</td>
<td>43594</td>
</tr>
<tr>
<td>r2</td>
<td>0.00158</td>
<td>0.00173</td>
<td>0.000140</td>
<td>0.000151</td>
</tr>
</tbody>
</table>

*p < 0.10, ** p < 0.05, *** p < 0.01. Robust standard errors are corrected for two-way clustering at the household level and caste in the village-year level.

The results are very similar to the ones in table 4.3. Columns 1 and 3 show that
having an OBC pradhan has a positive and significant impact on the probability of OBC to apply for reservations, both in the main (column 1) and broader (column 3) samples. Moreover, the estimated magnitude of the impact is very similar to the cross-sectional specifications. Columns 2 and 4 look at if the impact of having a pradhan from the same caste has changed over time. This is not the case, the interaction term between “having an OBC pradhan for OBC” and the time dummy is not significantly different from 0.

Both specifications (cross-section and panel) show that there is a significant and positive impact of having an OBC pradhan on the probability of OBC households of applying for reservations in jobs. The following section considers a more desegregated level, the jati level.

### 4.2 Impact of having a pradhan from the same jati

Section 4.1 underlines that OBC are more likely to apply for reservations in the public sector when the pradhan seat is reserved, and therefore occupied, by OBC. But who is concerned among OBC households? Does the positive impact of having an OBC pradhan concerns any OBC household or is it limited to the close social group of the pradhan, that is to say to people from his jati? Whatever the channel at stake here, the answer is not straightforward. While most of the literature underlines that the jati is still the real group of reference in contemporary India, Dunning (2010) shows that electoral quotas favor intra-caste solidarity. To get some insight into this question, I look at the impact of having a pradhan from the same jati on reservation application. I begin with a simple OLS specification:

$$ Y_{hjcv} = \alpha_0 + \alpha_1 X_{hjcv} + \alpha_2 CASTE_c + \alpha_3 E_{jcv} + \delta_v + \omega_{hjcv} \quad (4.3) $$

where $E_{jcv}$ is a dummy variable equal to one if the pradhan is from the same jati as the household and zero otherwise. The equation includes village dummies $\delta_v$ such that $\alpha_3$ is only estimated from intra-village variation. Standard errors are clustered at the level of $E_{jcv}$, that is to say at the level of the jati in the village.

The OLS results are shown in table 4.5. As expected, the relationship between application to job reservations and having a pradhan of the same jati is positive and significant (column 1). But this correlation may be driven by unobservables, so columns 2 to 5 test the robustness of the relation by controlling for additional factors. Column 2 controls for jati in the village level variables.\(^{13}\) Interestingly,

\(^{12}\)For recent works on the importance of jatis on diverse outcomes, see for example Damodaran (2008); Munshi (2011) or Munshi and Rosenzweig (2009).

\(^{13}\)The control variables at the jati in the village level are the mean age of households head in
Table 4.5: OLS estimation of the impact of having a pradhan from the same jati

<table>
<thead>
<tr>
<th>Dependent Variable: Application to reservations for jobs</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Same jati Pradhan</td>
<td>0.0317*</td>
<td>0.0384**</td>
<td>0.0555***</td>
<td>0.0496**</td>
<td>0.0609***</td>
<td>0.0217</td>
<td>0.0746*</td>
</tr>
<tr>
<td></td>
<td>(0.0175)</td>
<td>(0.0184)</td>
<td>(0.0235)</td>
<td>(0.0248)</td>
<td>(0.0208)</td>
<td>(0.0150)</td>
<td>(0.0415)</td>
</tr>
<tr>
<td>Same caste diff jati Pradhan</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HH controls</td>
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<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Village dummies</td>
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<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Jati in the vil. controls</td>
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<td>no</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Caste*District dum</td>
<td>no</td>
<td>no</td>
<td>yes</td>
<td>no</td>
<td>no</td>
<td>no</td>
<td>no</td>
</tr>
<tr>
<td>Caste*Village dum</td>
<td>no</td>
<td>no</td>
<td>no</td>
<td>yes</td>
<td>no</td>
<td>no</td>
<td>no</td>
</tr>
<tr>
<td>Jati dummies</td>
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<td>no</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>N</td>
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<td>14081</td>
<td>13086</td>
<td>14081</td>
<td>12867</td>
<td>12867</td>
<td>12867</td>
</tr>
<tr>
<td>r2</td>
<td>0.0632</td>
<td>0.0655</td>
<td>0.0681</td>
<td>0.0721</td>
<td>0.129</td>
<td>0.130</td>
<td>0.127</td>
</tr>
</tbody>
</table>

* p < 0.10, ** p < 0.05, *** p < 0.01. Robust standard errors are corrected for clustering at the jati in the village level. The sample in columns 5 to 8 exclude districts where there is only one village for which data are available, to keep some variation when the interaction term between caste and district dummies is added.

controlling for jati in the village variables increases the coefficient of the variable which indicates if the pradhan is from the same jati or not, and the coefficient becomes significant at a 5% level. This result underlines that the probability of having a pradhan from the same jati is correlated to jatis’ characteristics, but in a way that biases downward the coefficient on the variable of interest. This is consistent with the fact that households from jatis with a high status (positively correlated to the land owned by the jati) have a lower probability of applying for reservations, because of the stigma attached to reservations, but a higher probability of being elected (Gille, 2013). Column 3 controls for caste at the district level unobservables, by adding an interaction term between caste and district. As there is variation among households from the same caste in the variable of interest, it is also possible to control for caste in the village unobservables (column 4), in which case the impact is solely estimated from within caste in the village variation. Finally column 5 controls for jati unobservables. In all the specifications, having a pradhan from the same jati is positively correlated to applications for reservations in jobs. And once adding jati in the village controls, the coefficient on the jati of the pradhan is quite stable, between 0.04 and 0.06.

The results in section 4.1 also underline that having a pradhan from the same

the jati, their mean education level, the mean household size, the mean land owned by the jati in the village and the total number of households in the jati in the village.
caste has a positive impact only for OBC. To check if the results at the jati level are consistent with these previous results, I look at the heterogeneity of the impact across caste groups in column 6. The result is in line with what was obtained earlier. The fact that having a pradhan from the same jati enhances reservation application is only true for OBC. SC and ST do not seem to be affected by having a pradhan from their own group. Finally, if the impact of the pradhan only goes through jati networks, we also expect that having a pradhan from the same caste group but a different jati will have no impact. Column 7 considers this question. The coefficient is not significantly different from zero, showing that the increase in OBC reservations application when the pradhan is also an OBC is fully driven by an increase among households from the same jati.

The relationship between having a pradhan from the same jati and application to reservations for jobs is very robust to the addition of controls, and the level of the impact once controlling for some unobservables is much higher than when the impact is estimated at the caste level. It seems to confirm that the impact measured in tables 4.3 and 4.4 is an intra-jati effect. However, having a pradhan from the same jati is not random and may be correlated to characteristics of the jati in the village that cannot be observed and controlled for. Whereas controlling for village dummies in equation 4.1 was enough to control for the potential endogeneity of the caste of the pradhan, village dummies do not take into account the selection of someone from a specific jati within a given caste. So the OLS regressions in table 4.5 may not accurately estimate the coefficient. Therefore, the impact is now estimated using instrumental variables. The two stages are as follows.

First stage

\[ E_{jcv} = \pi_0 + \pi_1 X_{hjcv} + \pi_2 PR_{cv} + \pi_3 (PR_{cv} \times PROP_{jcv}) + \pi_4 PROP_{jcv} + \phi_j + \rho_v + \psi_{hjcv} \]  
(4.4)

Second stage

\[ Y_{hjcv} = \lambda_0 + \lambda_1 X_{hjcv} + \lambda_2 \hat{E}_{jcv} + \lambda_3 PROP_{jcv} + \Phi_j + \omega_v + \nu_{hjcv} \]  
(4.5)

The variable of interest, \( E_{jcv} \) is instrumented with two instruments. The first instrument is a dummy variable (\( PR_{cv} \)) which indicates if there is reservation for the caste group from which the household is from. Namely, the variable is equal to 1 if the household is OBC and the seat of pradhan is reserved for OBC and similarly for SC and ST. As seen in section 4.1, the fact that there is reservation for a specific caste group in the electoral term that is considered here may not be independent of caste level characteristics in the block (subdistrict). However,
reservations are not correlated with *jatis characteristics in the village*. It is therefore a valid instrument for $E_{jcv}$ and is expected to have a positive impact on $E_{jcv}$. The second instrument is the interaction of the reservation status of the caste group with the proportion in terms of number of households that the jati represents in the village ($PR_{cv} * PROP_{jcv}$). The underlining idea is that the impact of electoral reservations increases with the strength in terms of numbers that the jati has in the village. It is therefore also expected to have a positive impact on the probability of having a pradhan from the same jati. Because in itself the jati proportion may also impact the probability of applying for reservations, I control for $PROP_{jcv}$ in both stages. The second stage is similar to the OLS specification, but the impact of having a pradhan from the same jati is estimated with its predicted value $\hat{E}_{jcv}$. Standard errors are clustered at the jati in the village level.

Results are shown in table 4.6. The table shows three different specifications, where I allow the controls to vary. In column 1 and 2 the only controls are household level controls, jati dummies and village dummies. Column 3 and 4 additionally control for jati in the village variables and in column 5 and 6 an interaction term between caste and district is added. In the three first stages, the two instruments have a strong and positive impact on the probability that the household has a pradhan from the same jati. The p-value of the Hansen J-statistics also shows that the exogeneity of the instruments cannot be rejected. Looking at the second stages, having a pradhan from the same jati has a significantly positive impact on the probability of applying for reservations in the three specifications. The impact is quite large, it increases the probability of applying for reservations by 6 to 7 percentage points. It is also similar to what was estimated in the OLS regressions. Interestingly, the jati population share in the village is negatively correlated to reservation application. This is consistent with the results of table 4.3 which showed that the omission of jati level characteristics biases downward the impact of having a pradhan from the same jati.

There is no instrument to estimate the impact of having someone from the same caste group but a different jati. But the fact that the coefficient on the jati of the pradhan is much bigger than when the impact is estimated at the aggregated level indicates that much of the increase in reservation application, if not all, comes from households who are from the same jati as the pradhan.

---

14 The order in which electoral reservations for OBC are allocated to villages is related to the total size of the OBC population in each village. Jatis’ characteristics such as average education or economic strength are not related to the aggregate OBC population.

15 $PROP_{jcv}$ is the number of households from the same jati in the village divided by the total number of households in the village.

16 The interaction term is not correlated to jatis characteristics, once controlling for the independent effect of $PROP_{jcv}$. 

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Table 4.6: IV estimation of the impact of having a pradhan from the same jati

<table>
<thead>
<tr>
<th>Dependant Variable: Application to reservations for jobs</th>
<th>First stage</th>
<th>Second stage</th>
<th>First stage</th>
<th>Second stage</th>
<th>First stage</th>
<th>Second stage</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
<td>(6)</td>
</tr>
<tr>
<td>Same jati pradhan</td>
<td>0.0731***</td>
<td>0.0646***</td>
<td>0.0621**</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0201)</td>
<td>(0.0200)</td>
<td>(0.0257)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Same caste Reserv</td>
<td>0.188***</td>
<td>0.185***</td>
<td>0.271***</td>
<td>0.185***</td>
<td>0.271***</td>
<td>0.185***</td>
</tr>
<tr>
<td></td>
<td>(0.0665)</td>
<td>(0.0653)</td>
<td>(0.0806)</td>
<td>(0.0653)</td>
<td>(0.0806)</td>
<td>(0.0653)</td>
</tr>
<tr>
<td>Prop Jati * same caste Reserv</td>
<td>0.718***</td>
<td>0.689***</td>
<td>0.461**</td>
<td>0.718***</td>
<td>0.689***</td>
<td>0.461**</td>
</tr>
<tr>
<td></td>
<td>(0.258)</td>
<td>(0.257)</td>
<td>(0.222)</td>
<td>(0.258)</td>
<td>(0.257)</td>
<td>(0.222)</td>
</tr>
<tr>
<td>Prop Jati</td>
<td>0.0765</td>
<td>-0.0695**</td>
<td>0.211</td>
<td>-0.0721**</td>
<td>0.653***</td>
<td>-0.0318</td>
</tr>
<tr>
<td></td>
<td>(0.205)</td>
<td>(0.0276)</td>
<td>(0.238)</td>
<td>(0.0347)</td>
<td>(0.214)</td>
<td>(0.0394)</td>
</tr>
<tr>
<td>HH controls</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Village dummies</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Jati in the village controls</td>
<td>no</td>
<td>no</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Caste*District dummies</td>
<td>no</td>
<td>no</td>
<td>no</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Jati dummies</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>N</td>
<td>12867</td>
<td>12867</td>
<td>12867</td>
<td>12867</td>
<td>11992</td>
<td>11992</td>
</tr>
<tr>
<td>r2</td>
<td>0.312</td>
<td>0.0127</td>
<td>0.327</td>
<td>0.0131</td>
<td>0.538</td>
<td>0.0171</td>
</tr>
<tr>
<td>Instruments F-test</td>
<td>20.93</td>
<td>20.62</td>
<td>17.05</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hansen J-test (p-value)</td>
<td>0.229</td>
<td>0.172</td>
<td>0.223</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*p < 0.10, ** p < 0.05, *** p < 0.01. Robust standard errors are corrected for clustering at the caste in the village level. The sample is only using households from jatis present in at least two villages. In columns 5 and 6, I control for so the sample is further restricted to districts where there are at least two villages to have variation.

4.3 What drives the impact?

The fact that having a pradhan from the same jati enhances reservation application can be due to different factors. What inspired that paper is the idea that having a pradhan from the same jati makes it easier to access reserved jobs because the pradhan has political connections that he uses to help households from his jati. But other channels might explain the impact. The pradhan may increase the self-confidence of his jati fellows by showing that a low caste individual is able to hold a prestigious position. Or it can be simply related to information sharing. Having someone from the jati in a position with easier access to information may concretely help to apply for reservations. In this section, I discuss the three channels, and provide evidence that the help to access State institution is the only channel which can explain all the results.

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4.3.1 “Patronage democracy"

The first channel that I am exploring in this section is the one where the pradhan acts as an intermediary to help his jati fellows to get access to reservations. Political science and anthropological literature has emphasized that politicians in India have a great power over the distribution of resources because they control the bureaucracy (for a more detailed description of the phenomenon, see Chandra, 2004). This “patronage” system makes it complicated for poor people without connections to access State resources. Consequently, in rural India, there is an extensive usage of intermediaries (Manor, 2000; Witsoe, 2012). The pradhan plays an important role in this intermediation. Dunning and Nilekani (2013), in a survey from 512 villages in three Indian States (Karnataka, Rajasthan and Bihar), asked “to whom a hypothetical citizen would most likely turn for help getting access to a government benefit or service”. 73% of the respondents answered the council president. They were also asked “who has the most power to provide access to the desired service”. To this question 43% identified the president.

However, there may be a discrepancy between what individuals believe that the pradhan can do and what he can do in practice. Indeed, the pradhan can only help his jati fellows to get reservations in the administration if he is himself well connected. While high castes are historically well connected to the State and the political sphere, for low castes accessing power at a very local level it may not be the case. One way pradhans get access to higher levels of bureaucracy is through political parties. Political parties get involved in pradhans’ elections by financing their campaigns. In my sample, 2/3 of the pradhans currently in office have been financially supported for their campaigns by a political party. The proportion is the same for OBC pradhans.

I test the hypothesis that the positive impact of having a pradhan from the same jati is due to the pradhan helping households to get access to the State by looking at if the impact differs across pradhans financed by political parties and other pradhans. Namely, I interact the variable of interest with a dummy variable equal to one if the pradhan’s campaign was financed by a political party and zero otherwise. If the impact is due to patronage, then we expect the interaction term to be positive and significant. Table 4.7 shows the results for different specifications. Column 1 reproduces the results of the caste-level estimation in OLS; columns 2 and 3 show the OLS estimation of the jati-level estimation, and column 4 shows the IV estimation of the jati-level estimation.\(^{17}\) In the four specifications, the

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\(^{17}\)In the IV specification, both the “same jati pradhan” variable and the interaction term are instrumented. The strategy used is the one recommended by Angrist and Pischke (2008). More details are provided in the appendix as well as the two first-stage estimations.
### Table 4.7: Party support and job reservation application

<table>
<thead>
<tr>
<th>Dependant Variable:</th>
<th>Application to reservation for jobs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Estimation Method:</td>
<td>OLS (1) OLS (2) OLS (3) IV (4)</td>
</tr>
<tr>
<td>OBC reserv * OBC</td>
<td>-0.0207</td>
</tr>
<tr>
<td></td>
<td>(0.0159)</td>
</tr>
<tr>
<td>OBC reserv * Party * OBC</td>
<td>0.0665***</td>
</tr>
<tr>
<td></td>
<td>(0.0170)</td>
</tr>
<tr>
<td>Same jati pradhan</td>
<td>0.00404</td>
</tr>
<tr>
<td></td>
<td>(0.00697)</td>
</tr>
<tr>
<td>Same jati pradhan*Party</td>
<td>0.0873**</td>
</tr>
<tr>
<td></td>
<td>(0.0374)</td>
</tr>
<tr>
<td>HH controls</td>
<td>yes</td>
</tr>
<tr>
<td>Village dummies</td>
<td>yes</td>
</tr>
<tr>
<td>OBC*Party</td>
<td>yes</td>
</tr>
<tr>
<td>Caste in the village controls</td>
<td>yes</td>
</tr>
<tr>
<td>Jati in the village controls</td>
<td>no</td>
</tr>
<tr>
<td>Jati dummies</td>
<td>yes</td>
</tr>
<tr>
<td>Caste*District dummies</td>
<td>no</td>
</tr>
<tr>
<td>N</td>
<td>14081</td>
</tr>
<tr>
<td>r2</td>
<td>0.0638</td>
</tr>
</tbody>
</table>

*p < 0.10, **p < 0.05, ***p < 0.01. Robust standard errors are corrected for clustering at the caste (column 1) or jati (columns 2 to 4) in the village level. The sample in columns 3 and 4 is only using households from jatis present in at least two villages.

results are similar: the pradhan only has an impact on reservation applications to jobs when his campaign was financed by a political party. In other words, it is only when the pradhan is connected outside of the village through a political party that OBC tend to apply more for reservations. This result strongly supports the hypothesis of households applying more for reservations when they know that their pradhan can actually help them get the job.

But one can also think about other channels playing a role in the impact. In the two following subsections I question the channels of self-confidence and of information sharing.

### 4.3.2 An increase in self-confidence?

Another reason why the pradhan would enhance applications for reservations of his caste fellows is self-confidence. Psychological literature has underlined that social identity has an impact on performance because people tend to behave according to stereotypes. A reason why they do so is related to self-confidence. In an experiment conducted in India, Hoff and Pandey (2006) confirm that so-
cial identity measured by caste has an impact on low caste students’ behavior. Students from different caste groups were asked to perform a task. When their caste group was announced, low caste students were doing poorer than when they were anonymous. Discrimination against low castes seems to have been embodied such that low castes behave in the way people expect them to behave. This behavioral impact of discrimination could also lead low castes to negatively self-select themselves in the reservation application process.

Recent evidence has shown that stereotypes in India are changing and that reservations have a long lasting impact on the way people consider discriminated groups and on the way they consider themselves. Bhavnani (2009) and Beaman et al. (2009) show that quotas for women in Gram Panchayats have changed the probability that they run for office in unreserved panchayat and that they are actually elected. Similarly, reported crimes against women in India have increased with the implementation of reservations for women in Gram Panchayats, because the police is more willing to record those crimes, but also because women feel more confident to report them (Iyer et al., 2012). Chauchard (2010) provides evidence that having experienced a low caste pradhan diminishes discrimination against low castes in the village, and that this is partly due to a change in how their social status is perceived. He further underlines that the way they evaluate their own social status is positively changed. Having a pradhan from the same caste group may therefore change the behavior of low caste towards reservations through a change in the belief of what they can possibly achieve.

It can also be a confidence in institutions mechanism. In a cross-sectional setting, Bros and Borooah (2013) find that low castes groups have a higher confidence in institutions than high castes and attribute it to the policies that low castes can benefit from.

However, several results in this paper contradict the interpretation of the positive impact of having someone from your jati/caste as a pradhan as a “confidence impact”. The first obvious rejection of this channel is that, as shown in tables 4.3 and 4.5, the impact is restricted to OBC. Whereas we would expect that the role model channel has principally an impact on castes at the very bottom of the hierarchy, SC/ST pradhans do not have an impact on the application rate to reservations in jobs of their caste fellows. In columns 1, 2 and 3 of table 4.8, I also provide evidence that political reservations did not seem to have changed the way OBC feel discriminated. Finally column 4 in table 4.8 studies the im-

---

18 Households were asked if they have been discriminated against because of their caste while seeking job, or if they have been prevented from entering any street or place of worship within the village. The discrimination variable is a dummy variable equal to one if they answered yes to at least one of these questions.
### Table 4.8: The self-confidence channel

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>(1) Discrimination</th>
<th>(2) Discrimination</th>
<th>(3) App job reserv</th>
<th>(4) App job reserv</th>
</tr>
</thead>
<tbody>
<tr>
<td>Estimation Method</td>
<td>OLS</td>
<td>OLS</td>
<td>IV</td>
<td>OLS</td>
</tr>
<tr>
<td>OBC reserv * OBC</td>
<td>0.000777</td>
<td>0.0324</td>
<td></td>
<td>0.0324</td>
</tr>
<tr>
<td></td>
<td>(0.0181)</td>
<td>(0.00745)</td>
<td></td>
<td>(0.00745)</td>
</tr>
<tr>
<td>OBC prev Reserv * OBC</td>
<td></td>
<td></td>
<td>-0.0219</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.00943)</td>
<td></td>
</tr>
<tr>
<td>Same jati pradhan</td>
<td>-0.0409</td>
<td>-0.00845</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0275)</td>
<td>(0.0363)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>HH controls</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Village dummies</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Caste in the village controls</td>
<td>yes</td>
<td>no</td>
<td>no</td>
<td>yes</td>
</tr>
<tr>
<td>Jati in the village controls</td>
<td>no</td>
<td>yes</td>
<td>yes</td>
<td>no</td>
</tr>
<tr>
<td>Jati dummies</td>
<td>no</td>
<td>yes</td>
<td>yes</td>
<td>no</td>
</tr>
<tr>
<td>Caste*District dummies</td>
<td>no</td>
<td>no</td>
<td>no</td>
<td>no</td>
</tr>
<tr>
<td>N</td>
<td>14081</td>
<td>12867</td>
<td>12867</td>
<td>14081</td>
</tr>
<tr>
<td>r2</td>
<td>0.199</td>
<td>0.221</td>
<td>0.00451</td>
<td>0.0634</td>
</tr>
</tbody>
</table>

\* $p < 0.10$, \*\* $p < 0.05$, \*\*\* $p < 0.01$. Robust standard errors are corrected for clustering at the caste (columns 1 and 4) or jati (columns 2 and 3) in the village level. The sample in columns 3 and 4 is only using households from jatis present in at least two villages. The dependent variable in columns 1 to 3 is a dummy variable equal to one if a member of the household has suffered from discrimination while seeking jobs or has been prevented from entering a street in the village or a place of worship because of her/his caste.

The impact of previous reservations in elections for OBC. If the increased probability of applying for reservations in jobs is due to a better self-confidence, then we would expect the effect to last. However, the impact of previous reservations is negative. This result underlines that the impact of having an OBC pradhan increases the application rate of OBC during the electoral term, but decreases it afterwards. It shows that the impact is really related to the pradhan currently being in power.

#### 4.3.3 The information channel

Another way the positive impact of having a pradhan from the same caste/jati is the role that the pradhan may play in transferring information to his network. Applying for reservations in jobs is a complicated process. It requires to know how to get a “caste certificate”, which proves the caste identity of the applicant, and how to apply for quotas. The pradhan, because he is connected to the outside world, may be a source of information for his caste/jati.

But again, several results contradict the information channel as being the main channel driving the impact. First of all, if the pradhan is a source of information...
### Table 4.9: The information channel

<table>
<thead>
<tr>
<th>Dependant Variable:</th>
<th>Application to reserv. in schools</th>
<th>Applications to reserv. for jobs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Estimation Method:</td>
<td>(1) OLS</td>
<td>(2) OLS</td>
</tr>
<tr>
<td></td>
<td>(3) IV</td>
<td>(4) OLS</td>
</tr>
<tr>
<td></td>
<td>(5) OLS</td>
<td>(6) IV</td>
</tr>
<tr>
<td>OBC reserv * OBC</td>
<td>0.0103 (0.0180)</td>
<td>0.0540*** (0.0141)</td>
</tr>
<tr>
<td>Same jati pradhan</td>
<td>0.0110 (0.0272)</td>
<td>-0.0287 (0.0346)</td>
</tr>
<tr>
<td></td>
<td>0.0715*** (0.0224)</td>
<td>0.0750*** (0.0214)</td>
</tr>
<tr>
<td>OBC reserv * OBC * educ</td>
<td>-0.00526** (0.00235)</td>
<td></td>
</tr>
<tr>
<td>OBC * educ</td>
<td>0.00314 (0.00211)</td>
<td></td>
</tr>
<tr>
<td>Same jati pradhan * educ</td>
<td>-0.00235 (0.00150)</td>
<td>-0.00277 (0.00174)</td>
</tr>
<tr>
<td>HH controls</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Village dummies</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Caste in the village controls</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Jati in the village controls</td>
<td>no</td>
<td>yes</td>
</tr>
<tr>
<td>Jati dummies</td>
<td>no</td>
<td>yes</td>
</tr>
<tr>
<td>Caste*District dummies</td>
<td>no</td>
<td>yes</td>
</tr>
<tr>
<td>N</td>
<td>14081</td>
<td>12867</td>
</tr>
<tr>
<td>r2</td>
<td>0.291</td>
<td>0.332</td>
</tr>
</tbody>
</table>

* \( p < 0.10, \quad ** p < 0.05, \quad *** p < 0.01. \) Robust standard errors are corrected for clustering at the caste (columns 1 and 4) or jati (columns 2, 3 and 5, 6) in the village level. The sample in columns 2, 3, 5 and 6 is only using households from jatis present in at least two villages.

for his network and this is what increases the application to reservations in job, then we expect that the same happens to application to reservations in schools. Applying to reservations in school also requires a caste certificate, as well as a knowledge of the procedure. The only way in which application to reservations in jobs and application to reservations in school differ is through the admission process. Whereas access to reservation in schools is given through an anonymous competitive exam, the process to get a reserved job is discretionary. Table 4.9 shows the results of the same regression but the dependent variable is now application to reservations in school. As we can see in columns 1 to 3, there is no impact of having a pradhan from the same jati/caste on application to reservations for schools. One additional argument is that access to information is related to education (see Foster and Rosenzweig, 1995, for India for example). Therefore, if the information channel is driving the impact, we expect that the impact of the pradhan decreases with the education level of the household’s head. The

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19Low castes also benefit from quotas in higher education institutions. For more information, see Gille (2013).
rationale behind the second point is that the more the head of the household is educated, the less additional information is required from the pradhan, because the household already has a good access to information. Columns 3 to 6 in table 4.9 show the results of interacting the education level of the household’s head with the variable of interest. The impact of having a pradhan from the same caste for OBC seems to diminish with the education level of the household’s head (column 4). But this result is not robust when I only consider households from the same jati as the pradhan (columns 5 and 6). Therefore, the impact of having a pradhan from the same jati on reservations application does not seem to come from a better access to information.

5 Conclusion

The central empirical finding here it that sharing the ethnic group of the village council president increases households’ propensity of applying for reservations in the public sector. The use of the electoral quota system, which determines the caste group of the council president, to identify this impact, allows me to rule out that this due to caste specific unobservables. Indeed the interpretation the most consistent with the data is that it is due to a “patronage” system, where the council president helps the members of his jati to access reserved jobs in the public sector. The data reject alternative explanations such as an improved self-confidence or pure information sharing.

These findings have important policy implications. Although India is the country with the largest affirmative action program, many countries implement quotas for discriminated groups. One conclusion from this paper is that the implementation conditions matter a lot for the success of affirmative action. In this specific context, the fact that the hiring process is discretionary and that politicians have important power over bureaucrats does not provide equal opportunities of access to every eligible people. In practice, the reservation policy in the public sector is more beneficial to already connected people (who supposedly need less help) than to the very poor. The way this policy is implemented seems to have consequences conflicting with the original purposes of affirmative action policies.
Conclusion
Although Aristotle was already writing more than 2000 years ago that “Man is by nature a social animal”, the fact that human beings develop and behave according to others has been acknowledged in the economic literature only very recently. It is however important to take into account the social character of human beings, notably because it helps understanding behaviors which otherwise would seem irrational. The mechanism of stigma which prevents people from taking advantage of welfare take-up because they care about how others perceive them (and which is explored in chapter 3) illustrates the role that others can play in decision-making.

Taking into account the role of others is even more important in *development economics*, because of the specific institutional context. In particular, developing countries often have very binding social norms which have a strong impact on economic development. Untouchability in India is an example of a social norm which prevents the economic development of a very sizable share of the population. Far from having only a negative role, others can also compensate for problems inherent to developing countries such as market deficiencies. For example, the importance of informal social networks is often underlined in the context of credit markets.

This dissertation aims at providing some evidence of the role of social capital in India, with a focus on its relation with human capital. It explores the relation following two directions. First, in chapter 1 and 2, it looks at the impact of the human capital of others on aggregate and individual productivity. Second, in chapter 3 and 4, it looks at the impact that others have on human capital.

**Main findings**

The effect of others’ human capital is first studied in chapter 1 with a macroeconometric perspective. Using households level data aggregated at the State level in India, I explore how the distribution of education is related to income per capita. I find that a more unequal distribution of education is positively correlated to income per capita. However, the relation varies across States, and depends on the initial level of income. The main result is driven by richer States, whereas a more equal distribution of education seems to be better for poorer States.

The chapter also provides a first insight in the mechanisms that drive the relation. Theoretically the channels are threefold: there may be education spillovers, the returns to education may be non-linear, and/or there may be complementarity between workers education level. The results show that all the three channels seem to play a role in the relation.
Chapter 2 continues the study of the impact of other’s human capital on productivity, but this time with a microeconomic perspective. More precisely, I study the impact of the education level of members from the same caste in the village on agricultural productivity. I use household level data from the 17 major States of India.

I find that an increase in the average education level of members from the same caste in the village has a positive impact on households’ agricultural productivity. The impact solely comes from households in the caste who have agriculture as their main activity. Those who are not farmers have no impact. There is also heterogeneity in the impact depending on the cultivated crop: households cultivating rice benefit less from the education of their caste fellows than households cultivating wheat. This heterogeneity seems to be related to the extent to which learning about a given crop is possible. Furthermore, I am able to show that it is very unlikely that the positive impact of neighbors’ education is driven by caste unobservables. These results therefore provide support to the existence of education spillovers in agriculture.

The focus is different in chapters 3 and 4. I am interested in how others impact human capital accumulation, either directly as in chapter 3, or indirectly through others’ impact on available opportunities as in chapter 4.

Chapter 3 studies affirmative action programs (also called reservations) for low castes in higher education. The question I am asking in this chapter is how the application to quotas in higher education in India is affected by the fact that affirmative actions programs are highly stigmatized. To study this I use the same database as in chapter 2 and look at the impact of households’ social status on application to reservations. I find that application to reservations decreases with social status for the Other Backward Classes, a group of low castes. For the Scheduled Castes and Scheduled Tribes who are at the bottom of the traditional hierarchy, there is no impact of social status. I also find that the negative impact of social status for OBC is stronger for rich households. These results are consistent with a stigma effect in application for reservations in higher education. They are therefore confirming that others matter in education investment, because people seem to care about others’ opinion when applying to specific programs.

Chapter 4 is also concerned with affirmative action programs in favor of low castes. But in this chapter the focus is on quotas in public employment. Low castes have reserved jobs in the public sector, but the access is not easy as recruitment
is mainly discretionary. I am therefore interested in the role of caste networks in facilitating access to reserved jobs. To do this, I use the same dataset as in chapter 2 and 3, and look at the impact of having someone from the same caste at a local electoral position on the probability of applying for reservations in the public sector.

I find that having someone from the same caste as an elected leader has a positive impact on application for reservations in the public sector. The explanation of this impact which is the most consistent with the data is that local elected leaders help their caste fellows to get access to the jobs thanks to their own connections. The alternative explanations are not consistent with the empirical findings. This chapter therefore shows that peoples’ social capital, here the caste group, has an impact on individuals’ economic opportunities.

Discussion and ideas for future research

The four chapters of this dissertation are unanimous on the fact that human capital and social capital are strongly interrelated. This thesis therefore provides empirical support to the argument that the study of human capital requires an analysis which incorporates the others. In particular, chapters 1 and 2 underline that the role of others should be taken into account when measuring returns to education, because there are complementarities or externalities which can blur the true impact of human capital. But the impact of others on human capital related issues is not always as straightforward as one might think. Chapters 3 and 4 highlight that the impact of social capital on human capital formation can be indirect but nevertheless have important consequences. In the particular context of affirmative action for low castes in India, others matter because people care about what people around them think and because they have an impact on their job opportunities, and therefore on their expected returns to education. More elaborate ways of incorporating the role of others in the economic theory thus need to be invented.

However, incorporating others in the analysis of human capital also brings its share of surprises with results that the idealistic researcher would have preferred not to find. The fact that equality of education is associated with lower income per capita as shown in chapter 1 is hard to translate into policy advice. Similarly, finding that education spillovers do not cross caste boundaries in chapter 2 and therefore that low castes who are not well educated have no chance to benefit from more educated people from other castes does not give hope for the improvement of low castes economic status. Even the analysis of affirmative programs directly
targeted at improving low castes economic status in chapter 4 shows that State’s benefits are captured by castes that are well-connected.

Fortunately, all the findings are not negative. For example chapter 3 shows that one consequence of stigma in affirmative action is to prevent households with a high status to apply and therefore acts as a safety barrier against the “creamy layers”.

Moreover, the exploration of the link between human capital and social capital is far from being complete. This thesis only focuses on the educational component of human capital, but other dimensions of human capital may relate to social capital. For example, it has been shown that stigma is an obstacle to the enrollment in health related programs (Stuber and Kronebusch, 2004). But the relation between health and social capital does not always go in the expected direction. For example, Luke and Munshi (2007) show that low castes invest more in the health of their children than high castes, and that it is related to different returns to human capital across castes. Although their results are related to a specific context in South India, one should not underestimate the fact that social capital may relate differently to different components of human capital.

Similarly, this thesis approximates social capital by the network one is born with, which is the caste in India. However, social capital evolves along the life according to the relations that one engages in. It would be interesting to study how social capital is affected by economic and social mobility. In India for example, sociologists have underlined that scheduled castes having reached high positions thanks to affirmative action programs have cut off all relations with their caste. Bros (2013) shows that although caste is still a strong determinant of individuals’ perceived social status, income and education improve how people classify themselves. One can therefore think that approximating the network by the ethnic or caste group is good when groups are homogenous, but may not be such a good proxy when within-group inequalities increase.

Many other things can be done on the relation between human capital and social capital. Among them, further study of affirmative action programs is of great interest. In particular, one interesting question is how the impact of affirmative action programs such as quotas in education depends on preexisting social capital. In India for example, Deshpande and Newman (2007) describe how hard it is for scheduled castes who entered the university thanks to affirmative action programs to find jobs that match their education level and skills. The suggested reasons are that they lack the network and suffer from discrimination.
Bertrand et al. (2010) quantify the difference in terms of wages between quotas beneficiaries and the others in India, but to my knowledge no study directly assesses the role played by networks.

It is also essential to understand the general equilibrium effect of affirmative action programs. In India the implementation of quotas in higher education for OBC in 2006 led to an increase in the total number of seats available in universities. If quotas in education go along with a boom in the supply of educated workers it would inevitably have an impact on the labor market, in terms of wages for example. Although it may be hard estimate to this equilibrium effect empirically, a theoretical model could be a first step towards a better understanding of the global impact of affirmative action programs.

This thesis sheds some light on the relation between human capital and social capital, but many questions remain unexplored and I am merely mentioning few of them. But given the importance that this topic has, notably for the design of educational policies, new research should soon fill this gap.
Appendix
Appendix to Chapter 1
Table A1.1: Education attainment to years of education conversion table

<table>
<thead>
<tr>
<th>Educational attainment code</th>
<th>Imputed years of education</th>
</tr>
</thead>
<tbody>
<tr>
<td>Not literate</td>
<td>0</td>
</tr>
<tr>
<td>Literate through attending NFEC/AEC, TLC or others</td>
<td>1</td>
</tr>
<tr>
<td>Literate, but below primary</td>
<td>3</td>
</tr>
<tr>
<td>Primary</td>
<td>5</td>
</tr>
<tr>
<td>Middle</td>
<td>8</td>
</tr>
<tr>
<td>Secondary</td>
<td>10</td>
</tr>
<tr>
<td>Higher secondary</td>
<td>12</td>
</tr>
<tr>
<td>Graduate and above</td>
<td>15</td>
</tr>
</tbody>
</table>

Note: NFEC, non-formal education centre; TLC, Total Literacy Campaign; AEC, alternative education centre
Source: Kingdon and Theopold (2008)
Appendix to Chapter 3
Figure A3.1: States in the sample
Appendix to Chapter 4
Table A4.1: Differences in means across reservation status

<table>
<thead>
<tr>
<th></th>
<th>SC</th>
<th>ST</th>
<th>OBC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>0.180</td>
<td>-0.234</td>
<td>-0.0576</td>
</tr>
<tr>
<td>Sex</td>
<td>-0.00111</td>
<td>0.0221</td>
<td>-0.00113</td>
</tr>
<tr>
<td>Years of educ</td>
<td>0.183</td>
<td>-0.236</td>
<td>-0.0584</td>
</tr>
<tr>
<td>HH size</td>
<td>-0.112</td>
<td>0.0556</td>
<td>0.0421</td>
</tr>
<tr>
<td>Land</td>
<td>0.0114</td>
<td>-0.0593</td>
<td>0.000471</td>
</tr>
<tr>
<td>Income</td>
<td>-818.5</td>
<td>5032.4</td>
<td>-128.9</td>
</tr>
<tr>
<td>Agr activity</td>
<td>0.00180</td>
<td>-0.0352</td>
<td>0.00178</td>
</tr>
<tr>
<td>Irrig. Land</td>
<td>-0.0875</td>
<td>0.229</td>
<td>0.0196</td>
</tr>
<tr>
<td>Observations</td>
<td>3685</td>
<td>820</td>
<td>8945</td>
</tr>
</tbody>
</table>

*p < 0.10, ** p < 0.05, *** p < 0.01. The table compares the means of various household level variables across villages with different reservation status for the position of pradhan, once controlling for caste*district dummies. For example, column 1 compares variables means in villages where the pradhan position is reserved for SC with variables means in villages where the pradhan is not reserved for SC. Only the differences in means are reported, because once controlling for caste*district dummies, the means in itself are not informative. t statistics are in parentheses.

The strategy to instrument the variable “Having a pradhan of the same jati” and its interaction with the variable indicating if the pradhan’s campaign was financed by a political party in section 4.3.1 or with education in section 4.3.3 follows the suggestion in Angrist and Pischke (2008). I provide hereafter the details for the estimation in section 4.3.1, but the strategy is exactly the same in section 4.3.3. I first estimate

$$E_{jcv} = \pi_0 + \pi_1 X_{hjcv} + \pi_2 PR_{cv} + \pi_3 (PR_{cv} \ast PROP_{jcv}) + \pi_4 PROP_{jcv} + \phi_j + \rho_v + \psi_{hjcv} \quad (A4.1)$$

as in section 4.2. I then use the predicted value, $\hat{E}_{jcv}$ from (A4.1), and its interaction with the dummy indicating if the campaign was financed by a political party $PARTY_v \ast \hat{E}_{jcv}$ as instruments in the two first-stage estimations of $E_{jcv}$ and $PARTY_v \ast E_{jcv}$ respectively (A4.2) and (A4.3) below, in a conventional 2SLS procedure.

$$E_{jcv} = \delta_0 + \delta_1 X_{hjcv} + \delta_2 \hat{E}_{jcv} + \delta_3 PARTY_v \ast \hat{E}_{jcv} + \delta_4 PROP_{jcv} + \gamma_j + \eta_v + \mu_{hjcv} \quad (A4.2)$$

$$PARTY_v \ast E_{jcv} = \epsilon_0 + \epsilon_1 X_{hjcv} + \epsilon_2 \hat{E}_{jcv} + \epsilon_3 PARTY_v \ast \hat{E}_{jcv} + \epsilon_4 PROP_{jcv} + \kappa_j + \mu_v + \nu_{hjcv} \quad (A4.3)$$

$\gamma_j$ and $\kappa_j$ are jati dummies, $\eta_v$ and $\mu_v$ are village dummies and $\mu_{hjcv}$ and $\nu_{hjcv}$ are error terms. The estimation results of equations (A4.2) and (A4.3), as well as the first-stage estimations for the IV estimation in section 4.3.3 are reported in table A4.2. The estimation of (A4.1) is not reported because it is the same as in table 4.6.
Table A4.2: First-stage estimations

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>First-stages table 4.3.1</th>
<th>First-stages table 4.3.3</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>$E_{jcv}$</td>
<td>1.115***</td>
<td>0.178</td>
</tr>
<tr>
<td></td>
<td>(0.175)</td>
<td>(0.114)</td>
</tr>
<tr>
<td>$PARTY_v \times \hat{E}_{jcv}$</td>
<td>-0.191</td>
<td>0.804***</td>
</tr>
<tr>
<td></td>
<td>(0.116)</td>
<td>(0.0882)</td>
</tr>
<tr>
<td>$educ_{h,jcv} \times \hat{E}_{jcv}$</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HH controls</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Village dummies</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Jati in the village controls</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Jati dummies</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>N</td>
<td>12867</td>
<td>12867</td>
</tr>
<tr>
<td>r2</td>
<td>0.339</td>
<td>0.476</td>
</tr>
<tr>
<td>Instruments F-test</td>
<td>20.98</td>
<td>49.23</td>
</tr>
</tbody>
</table>

*p < 0.10, **p < 0.05, ***p < 0.01 Robust standard errors are corrected for clustering at the caste (columns 1 and 2) or jati (columns 3 and 4) in the village level. The sample is only using households from jatis present in at least two villages.
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