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GENDER PARITY IN HIGHER EDUCATION ENROLMENT: ROLE OF FAMILY NETWORKS

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Abstract

Unlike primary or secondary education, higher education is not considered compulsory and hence it becomes a matter of individual choice to pursue higher education and the subject of specialization. This study examines the role of a form of social capital as in a family's social networks to a doctor, an educationist or a government official in improving gender parity in higher education, as well as into the arts/non-arts streams in India. The empirical analysis based on IHDS data for the years 2005/06 and 2011/12 shows that gender differences in enrollment and the role of social networks is statistically significant in the context of the stream of enrolment but not for college enrollment. Female students in comparison to male students have lower odds of enrolling into a non-arts field, relative to arts field. However, females with networks have higher odds of enrolment into a non-arts stream relative to females without networks. Lastly, if this social connection happens to be with a woman then the chances of enrolment for females into the non-arts stream improves relative to female students with other networks or male students.

Key words: *Higher Education, Gender Parity, Family Networks, Arts and Non-arts stream*

JEL Codes: *I23, J16, N30, P36*

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INTRODUCTION

Over the years, primary and secondary school education in India has received large amounts of investment and attention that has led to their Gross Enrollment Ratios (GER) being equal to nearly a 100 percent. However, a brief look at higher education (or tertiary school) enrollment rates tells us a very different story. According to the latest All India Survey on Higher Education (AISHE) report (GoI, 2019) the GER for higher education, calculated for the 18-23 age group, is 26.3 percent. Disaggregated in terms of gender, it is 26.3 percent for males, and 26.4 percent for females. This is nearly at par and at first look with 48.6 percent of females in higher education does not seem to suggest a gender bias. However, this aggregate number hides a large problem of large gender gaps at the stream-wise college enrollment level. We see a large and persistent gap in enrollment into professional courses where the female constitute 28 percent in Engineering or 34 percent in Law and 53 percent in Arts while favoring females in Medicine (60 percent) due to a very high sex ratio of 350 women per 100 men in nursing[1]. Such gender gaps in enrolment for streams (fields of study) that are considered 'more quantitative' is well established in previous literature (Card and Payne, 2017). These fields are specifically applicable to STEM courses- Science, Technology, Engineering and Mathematics.

This study tries to understand the gendered gap across academic streams/fields by examining the role of social capital. Financial capital and human capital are most often used to understand and contextualize enrollment related questions. Since it is a matter of individual choice to pursue higher education, such decisions are affected not only by financial and human capital, but also social capital. Coleman (1988) argues that financial and human capital should be supplemented by social capital to explain human choices. Social capital

[1] These numbers should be viewed with caution as they are self-reported and might not be the actual estimate of enrollments in the country. However, this is the only data available for India and thus we report it.

could accrue through something as vague as family structure, or something as specific as the number of resourceful people the family has access to. Social capital could thus entail of and mean several things, however just like in Myroniuk *et. al.* (2017), this study restricts the definition of social capital to a single aspect- that of social networks

Specifically, it looks at the household's social networks, *viz*. if the household personally knows anyone who works in an *educational institute, medical organization or is a government servant* based on India Human Development Survey (IHDS) dataset (Desai and Vanneman, 2014 and Desai *et. al.,* 2007) to analyse the variations in women's access to higher education. We hypothesize that the choice to enroll into a non-arts field is especially driven by having access to these kinds of networks. This study has three main results: a baseline result of the effect of gender on enrollment; a result using the interaction of networks and the gender of the individual; and finally, a result for interaction of the gender of the network and the gender of the individual. It finds that without accounting for networks, female students have significantly lower odds of enrolling into a non-arts field, relative to male students. However, females with some networks have higher odds of enrollment relative to females with no networks. It also looks at each of these networks separately, and finds that female students who have networks with female teachers have positive odds of enrollment into a non-arts field, relative to everybody else (female students with other networks and male students). It thus finds that these types of personal relationships do seem to have a significant effect in determining the individual's choices, even after controlling for individual, household and regional factors. This paper thus contributes in understanding gender parity in higher education spaces in India, and suggests that a policy level understanding of networks could boost such enrollment.

This study deals with some endogeneity concerns by exploiting the panel data nature of the IHDS. The IHDS I (Desai *et. al.,* 2007) was conducted in 2004-05 and in 2011-2012, the same households were re-interviewed for IHDS II (Desai and Vanneman, 2014). A potential concern is that those who are enrolled in college or in a non-arts stream have more networks because they are enrolled in an institution. However, due to the availability of panel data, we use social networks from the previous round to predict enrollment in IHDS II. We also use a large set of control variables from the previous round so as to avoid the possibility that enrollment in IHDS II was influencing any control variable to be higher or lower. IHDS is the only such large scale panel study in India, and its unique nature is what allows for such an examination. It is thus striking that these results remain after controlling for a host of other human and financial capital. We control for scores obtained in the higher secondary examination, family income, mother's education, caste and even the average education of the area the household lives in.

Social networks turn out to be an important factor in stream based enrollments because of the nature of the perception around 'Arts' being an easy stream and meant for girls in India. Nair (2010) notes that even within vocational and training based courses, courses for women tend to cater to their 'domestic' role rather than their 'productive' role and reinforce the notion of them primarily being caregivers and child bearers. Having contacts could have some influence on such educational decisions, through various channels. For instance, if an individual knows someone who has a good job, they could help the individual in the process of enrolling and/or could also convince the individual's parents into letting them enroll. This might be a distinct advantage over someone who doesn't know anyone. There could also be an alternative role model channel. In a conventional cost-benefit approach this could also be motivated as follows: households will only enroll their children into college and into STEM if the net benefit of doing so is greater than the net benefit of not enrolling. This net benefit of enrollment consists of actual as well as opportunity costs. In a society where girls have been shown to disproportionately bear the burden of household chores, Nair (2010) argues that enrolling them into ‘harder’ fields will presumably reduce the time they have for these activities, increasing their opportunity cost of schooling. Parents may also assume that girls get lower labour market returns for higher education, and this might reduce their perceived benefit of schooling. The unknowns in STEM could increase perceived costs. However, having access to contacts or people could also increase the perceived benefits of enrollment, as parents could gain information through their networks and realize the actual potential of schooling. Social networks could also help uneducated parents[2] to understand the formal education system better, and could also help households establish informal contacts in universities and the labour market, which might in turn help enrollment as well as employment.

Most literature on education in India has been focused on primary education. Agarwal (2006) argues that in the absence of good data, there is very little public debate on higher education. Additionally, higher education is riddled with systemic deficiencies that lead to large ethnic, income and gender inequalities. In this study we intend to focus on higher education, specifically, on enrollment into college and into a ‘non-arts stream’, in order to understand the role of social networks in explaining gender differences in enrollment. The characteristics affecting enrollment at this level could be different from those affecting primary school enrollment, mainly because the sample at this level consists of individuals who have already finished 10th grade. Thus, they presumably have higher motivation, higher aptitude and higher family support compared to those who dropped out before 10th grade, and thus might face a different set of constraints. This paper will be able to look at the effect social capital has on increasing enrollment, while explicitly controlling for aptitude. Examining tertiary school enrollment is also crucial because, as seen in Table 2, in the early 1990s, India was ahead of China in both GDP growth rate and tertiary school enrollment.

[2]Some states in India have financial aid for first generational learners enrolled in undergraduate courses to encourage their enrollment into higher education. See: https://cms.tn.gov.in/sites/default/files/documents/higher_education_7.pdf

However, in 2016 while India's GDP growth rate is still higher than China's, their tertiary school enrollment is nearly double that of India's. There is substantial literature stating that private returns to secondary and tertiary levels of education are much higher than those of primary levels of education (Psacharopoulos and Patrinos, 2018). Psacharopoulos and Patrinos (2018) also go on to say that 'education remains a positive, significant, and profitable investment for individuals. On average, another year of education produces a private rate of return to schooling in excess of 5 percent to 8 percent a year. As such, there are few better investments one can make'. Education is also intrinsically essential and affects economic growth positively (Glewwe, 2002).

Our conceptualizing of social networks is very similar to Myroniuk *et. al.* (2017). They also define social capital as having contacts in the formal sector, such as knowing someone who is a teacher or a doctor. Thus they find that having a good social network is important in the subsequent development of human capital, and that in a developing country like India, where parents may have none to very little education, knowing someone who is well educated, increases their chances of obtaining a higher education too. While they are not able to establish a mechanism through which this effect takes place, they are able to establish that institutional connections influence the creation of human capital and not the other way around. There could be several mechanisms at play here. Such as, having connections acts as a 'role model' effect for students, or the presence of a social network gives the student a feeling of improved future labour market outcomes. The Myroniuk *et. al.* (2017) study is perhaps the first one to be able to effectively conceptualize and capture the effect of social networks on higher education in India. Our study extends the analysis in Myroniuk *et. al.* (2017) to specifically analyse the role of the gender of the household's social networks while it also controls for the self-reported grades obtained in the 12th standard examination as a proxy for aptitude and motivation towards continuing formal education.

The study is organized in the following manner. The first two sections review the literature on social capital and years of schooling, and gender and science education respectively. This is followed by a brief overview of the higher education enrollment in India and the objective of this study. This is followed by a section on description of the variables and the dataset used and then a section on the methodology used in this analysis and the main findings with last concluding section.

Social Capital and Years of Schooling: Theoretical Motivation

Human capital increases worker productivity and is valued in the market because it increases firm's profits and this human capital is different for different individuals. Acemoglu and Autor (2009) identify five sources of differences between human capital: innate ability, schooling, school quality, training and pre-labour market differences. Innate ability refers to an inherent predisposition that might make one individual 'smarter' than the other despite having similar human capital investments. Schooling is observable and can thus be easily accounted for. School quality is slightly harder to capture as it consists not only of school infrastructure, but also the skills of teacher; and training refers to the training given by firms to the workers they have hired. Pre-labour market differences refer to peer group effects or community level effects.

The idea of social capital is close to this understanding of pre-labour market differences. Social capital refers to the relationships and social structures that shape and enhance human capital for an individual (Schuller, 2001). Such relationships are between different groups as well as within groups, and could be in the form of norms, or in the form of social networks (Coleman, 1988). Thus an individual, who migrates to an area where the sense of community is very strong, could now have access to better networks and thus have stronger social capital. Coleman (1988) also uses the number of siblings a child has as a proxy for the amount of attention a child receives. He finds that for children with more siblings, the probability of dropping out of school was higher and that younger siblings in larger families were found to be associated with weaker educational outcomes. These types of features thus capture something very different from financial or human capital. It captures interpersonal relationships and the huge role such relationships might play in the choices individuals make. In this study we draw from such an idea of 'networks' in order to analyze this empirically. Our study uses a secondary database that asks households on whether they have any personal connections with people working in stable, well-reputed jobs. This could serve as a proxy to explore the nature of networks and human resources the household has access to and its association with the choices on higher education enrolment.

Social networks in the context of educational achievement have received a lot of interest of late. It captures the idea that there could be other channels, apart from policy, that influence enrollment into school and college. This channel comes through from living in tightly woven communities or through the social networks a household has access to. In a community centric society like India (Munshi and Rosenzweig, 2016), social networks could be an important factor in determining if and where households choose to enroll their children. Myroniuk *et. al.* (2017) finds that social capital effectively predicts the probabilities of individuals completing secondary school, enrolling into college and enrolling into a specific science or engineering course.

However, networks could also work in the opposite direction. For instance, Munshi and Rosenzweig (2006) examine school enrollment and caste in the city of Mumbai. They find that lower-caste boys have close networks with other male, working-class and lower-caste workers due to participation in the labour market. Such networks channel boys into the same traditional occupations as their networks. Lower caste girls, on the other hand, had historically low labor market participation rates and did not have these networks, these girls are thus able to switch to English schools and rapidly take up new jobs that allow them higher incomes. Thus *not* having networks proved to be useful and helped them into better occupational outcomes. Thus while networks could have positive effects, they could also have negative effects, and pull the individual away from better outcomes. Networks could also thus be used for career-related outcomes.

Alongside social networks, there are several other household level variables that could have significant effects on enrollment. These include wealth (Glewwe, 2002), intergenerational effects (Dreze and Kingdon, 1999) and social groups (Borooah and Iyer, 2005; White *et. al.*, 2016). These intergenerational effects are largely seen through the mother's education, where even basic education given to mothers has a large effect on enrollment. There are also significant differences seen in urban and rural areas (Duraisamy, 2002). For instance, educational facilities such as better quality schools, reduced distances to schools etc. had no effect on enrollment in urban areas, but turned out to be an important factor in rural areas (Glewwe, 2002). Similarly Azam and Kingdon (2013) finds that urban areas were dominated by private schools, and rural areas by government schools. Since the quality of education in these schools can be vastly different, educational outcomes of children could also vary due to the kind of area that they live in.

Gender and Science Education

The gender gap in science based fields has been a long standing debate, with some of the earliest voices being that of sociologists. In his seminal work, Chambers (1983) uses the famous 'Draw a Scientist test' using 4800 children as a sample, and follows them through kindergarten to 5th grade. He notes that stereotypes start emerging and becoming rigid as kids grow older and overall, only 28 women scientists were drawn and all of them by girls. Girls were also less likely to associate science with war and more likely to fear accidents related to scientific experiments. This is corroborated by Jones *et. al.* (2000), who find that the image of a 'mad scientist' is only perceived in the masculine context. Female students tended to want to help or make a change, and seemed to care more about the environment and animals, something they viewed as being inconsistent with subjects such as physics or chemistry. A significantly large gap also emerges when students describe their out-of-school experiences with science. Boys were encouraged to create, use mechanical instruments, batteries, fuses etc.; while girls reported being exposed to sowing seeds, making bread etc. More recently, Friedman-Sokuler and Justman (2016) study mathematical aptitude and enrollment into science streams in Israel, where they are able to examine cultural differences between Jewish and Arabic communities. They find that girls from the Arabic part did better at Math and enrolled in more science specific courses compared to girls in the Jewish part. They conclude that gender stereotypes that associate science with men could be weaker in Arab society. It could also be that return to female education could be larger in the Arab marriage market.

Women themselves could also make choices that reinforce this gender stereotyping if they operate with the notion that the job market might not have a place for them. Thus, a host of gendered norms, preferences and stereotypes driven by culture and family behaviour could be driving this gap. Carrell *et. al.* (2010) find that the gender gap in STEM classes *disappears* when high performing female students are assigned to female professors. Recently, Mansour *et. al.* (2020), using data from the United States Air Force Academy find that when high-ability female students are assigned a female professor, the probability that they work in a STEM field, and receive a STEM master's degree significantly increases. In the Indian context, Muralidharan and Sheth (2016) examines the role of teachers on test scores among school; children. They study Math and English scores of students in Andhra Pradesh and find that teachers do better at teaching students of their own gender however female teachers do better at teaching both girls and boys. Thus, they recommend that hiring female teachers might solve some of this gap in student achievement.

Studies focusing on the role of networks as well as on gender differences in enrolment largely pertain to school education and only a few of them are on India. The reason for a limited number studies on India could be that only recently India has achieved complete enrolment in primary schooling while GER in secondary schooling is yet to be 100 per cent. Given that tertiary schooling would require completion of prior schooling so for a large number of young adults the enrollment into higher education is not yet relevant and hence the challenges that come with it. Also, until recently higher education has been accorded limited priority for public policy intervention to address the disparities in enrollment across gender, caste and region and other regulations regarding access and quality.

Private returns to secondary and tertiary levels of education are much higher than those of primary levels of education making the pursuit of higher education a "profitable investment for individuals" (Psacharopoulos and Patrinos, 2018). For a populous developing country like India with a rising share of population in 18-25 years of age the aspirations for higher education are on the rise as the returns to higher education is more than three times that of basic schooling (Mahambre *et. al.,* 2021 and Rathore and Bhattacharya, 2018). On the other hand, education is also intrinsically essential and affects economic growth positively (Glewwe, 2002). Higher education institutions are considered important for innovations which in turn improve economic growth and that better skilled also have higher private returns. So both public policy (NEP, 2020[3]) and private individuals (a large demographic dividend) are beginning to see more benefit in investing in higher education creating a higher demand for education and the need to fulfill aspirations. Thus a study of factors that enable access to higher education could also provide useful inputs for the supply of more and better quality higher education and to analyse the pathways through which biases or prejudices against a segment of the population can be addressed.

[3] See https://www.education.gov.in/sites/upload_files/mhrd/files/NEP_Final_English_0.pdf

The focus of this study is to understand if there are differences in enrolment between male and female students after controlling for individual, household and regional factors. The study then attempts to capture the role of family networks in enrollment into higher education within female students. Lastly, the study attempts to assess if the association between female enrollments into non-arts stream is stronger when the contact individual is also a female. The analysis is based on two period panel data that allows us to control for potential endogeneity in some of the variables by using the information from the previous period. The present study differs from a previous study by Myroniuk *et. al.* (2017) on a similar issue and using the same data, in (a) including the gender of the social contact in the network and its relevance for enrollment of female students, (b) explicitly controlling for the aptitude of the student based on the self-reported ranking by the student in the higher secondary examination (HSE) of school completion; and (c) the average years of schooling of the adults in their village or urban block (primary sampling unit) of the enrolled individual to account for supply of higher education.

The next section gives a broad picture of higher education enrollment in India in recent years and some gendered aspects.

Higher Education in India: Trend and Pattern of Enrollment

Over the years, primary and secondary school education in India has received large amounts of investment and attention that has led to 100 percent GER as indicated by the World Development Indicators. However, tertiary school enrollment rates are about 26 percent in India compared to the world average of 38 percent with the highest rate at about 70 percent. According to the latest AISHE report the GER for higher education, for the 18-23 year age group is 26.3 percent (GoI, 2019).

The United Nations statistics shows that in most countries of the world the gender parity index is much larger than one and exceeding 2 or 3 for several countries. However, the enrolment is biased against women enrolling into streams that are considered ‘more quantitative’, or specifically STEM courses- Science, Technology, Engineering and Mathematics (Card and Payne, 2017). AISHE report for India shows that the ratio of girls to boys in enrollment is close to or slightly higher than 1 for most Indian states in India, indicating access to girls is as good as it is for boys. Disaggregated in terms of gender, it is 26.3 percent for males and 26.4 percent for females; and at first look does not seem to suggest a gender bias. However, this aggregate number hides a problem of large gender gaps at the stream-wise college enrollment level. Table 1 shows enrollment percentages for females across different educational streams. We see a large and consistent gap in enrollment into professional courses (Engineering, Management, Law) and a large gap favoring females in Medicine[4]

[4] These numbers should be viewed with caution as they are ‘self-reported’ and might not be the actual estimate of enrollments in the country. However, this is the only data available for India and thus we report it.

Table 1: Percentage Share of Female Students Across Streams and Over Time

Stream	2011-12	2012-13	2013-14	2014-15
Arts	51.1	52.3	53.0	53.1
Commerce	44.1	45.6	45.0	45.5
Science	48.8	48.3	47.0	47.6
Engineering	28.5	28.8	28.0	28.0
Management	35.6	35.3	36.8	36.5
Medicine	60.8	60.6	62.6	60.7
Law	32.0	31.9	32.2	31.1
All Streams	45.0	45.0	46.0	45.5
Stream	**2015-16**	**2016-17**	**2017-18**	**2018-19**
Arts	52.9	47.1	47.1	53.04
Commerce	46.2	53.8	52.5	48.8
Science	47.8	52.9	52.4	51.7
Engineering	28.0	28.4	28.6	28.0
Management	36.5	63.5	60.7	41.6
Medicine	61.1	38.9	61.3	60.6
Law	33.3	31.4	32.4	33.6
All Streams	46.2	53.8	53.2	48.6

Source: Various reports of AISHE, Ministry of Human Resource and Development, Government of India.

Most literature on education in India focuses on primary education. Agarwal (2006) argues that in the absence of good data, there is very little public debate on higher education. They also argue higher education is riddled with systemic deficiencies that lead to large ethnic, income and gender inequalities. The characteristics affecting enrollment at this level could be different from those affecting primary school enrollment, mainly because the sample at this level consists of individuals who have already finished 10^{th} grade. Thus, they presumably have higher motivation, higher aptitude and higher family support compared to those who dropped out before 10^{th} grade, and thus might face a different set of constraints.

Examining tertiary school enrollment is also crucial because, as seen in Table 2, in the early 1990s, India was ahead of China in both GDP growth rate and tertiary school enrollment. However, in 2018 while

India's GDP growth rate is still higher than China's, their tertiary school enrollment is nearly double that of India's. One of the reasons for this differential performance between India and China in tertiary school enrollment could be China's population policy when the share of 18-23 year olds in China was about 13 percent in the 1990s and decline to 7 percent in 2018. In contrast, a constant share of about 11 percent for 18-23 year olds in India between 1990 and 2018 with a low and stagnant public expenditure share of education in India's GDP creates supply shortage and a higher price for tertiary education. China's economic growth reduced poverty rates dramatically from 66 percent (47 percent) in early 1990s to 0.6 percent (22.5 percent) in 2018 and an important reason for that was the labour intensive nature of economic growth. This would have created the demand for tertiary education in terms of employability and higher per capita incomes leading to better affordability in China. India's capital intensive jobless growth did not lead to a similar path of improving tertiary enrollment as China's (Tejani, 2016).

Table 2: Tertiary School Enrollment: India and China

Country	Variable	1990	2000	2010	2018
China	GDP growth rate	3.91	8.49	10.64	6.1
	Tertiary school enrollment	**3.91**	7.62	24.05	50.06
India	GDP growth rate	**5.53**	**3.84**	**10.26**	**6.8**
	Tertiary school enrollment	**5.96**	9.55	17.91	28.06

Source: World Bank Database.

The AISHE data (collected by MHRD) on enrollments by the educational institutions is not mandatory reporting by an educational institution and hence there could be possible data gaps across regions or streams of education. Further the institution level information will not be able to inform us on the household or individual level preferences and constraints on accessing higher education. Such information is available in household survey based data sets of the

National Sample Survey Organisation and the IHDS. The IHDS is more suited for this analysis as it is a panel data unlike a single cross-section data of the NSSO and hence causal effects can be better measured using the panel nature of the data set. IHDS also have a more detailed set of questions on network and empowerment alongside individual and family characteristics. This enables to carry out the analysis as proposed in the objective of the study. The next section discusses the econometric methodology followed by a discussion of the covariates used in the models.

Methodology

The main aim of the analysis is to understand the role of social capital or the family's network variables that would be associated with the observed outcome of (a) college enrollment and (b) enroll in a non-arts stream. Underlying this observed outcome is the binary discrete choice to enroll (or not) in college/non-arts stream and hence the appropriate estimation methodology is the logit regression model as specified below.

$$Y_i = \Lambda(\beta_1 + \beta_2 Female_i + X_i\boldsymbol{\gamma}) \qquad (1)$$

Where, $\Lambda(z)=\frac{e^z}{1+e^z}$; and z= $\beta_1 + \beta_2 Female_i + X_i\boldsymbol{\gamma}$

The outcome variable (Y_i) is equal to 1 if an individual 'i' is enrolled in college and 0 if she is not. Similarly, it is equal to 1 if an individual 'i' is enrolled in a non-arts stream and 0 for those enrolled into arts and excludes those not enrolled in college. $Female_i$ is 1 for females and 0 for males. $\boldsymbol{X_i}$ is a vector of explanatory variables that includes individual, household and area level variables (details are presented in the next section) and $\boldsymbol{\gamma}$ is the vector of associated parameters.

The fitted Y values in a logit model are interpreted as the (predicted) probability that Y_i takes the value 1 corresponding t enrollment. Using the logits $\Lambda(z)=\frac{e^{z}}{1+e^{z}}$ the logit model in (1) is also expressed as odds ratio $\Omega(\mathbf{Z}_i)$:

$$\Omega(\mathbf{Z}_i)= \frac{p_i}{1-p_i} = \exp(z) \text{ so that } \frac{\Omega(z_2+\delta,\ldots.,z_k)}{\Omega(z_2,\ldots.,z_k)} = e^{\beta_2} \text{ if } \delta=1 \quad (2)$$

In this context, if z_2 is the variable *Female* in equation (1) above then odds ratio compares the female enrollment ($\delta=1$) with male (z_2 or *Female* =0) enrollment. The odds would be in favour (not in favour) of female enrollment and hence more (less) than 1 if β_2 is positive (negative). This interpretation is applicable to any of the regressors in the model and δ could be chosen to suit the context of discussion. All the results reported are odds ratios and implicit in that, is that the estimated coefficient would be positive if the reported values in the tables are greater than 1 implying that the odds are in favour of the characteristics when $\delta=1$. The discussions in this section however, would discuss the possible sign of the coefficient in the econometric specifications rather than for the odds ratio as mentioned in (2). Further, in the logit model of college enrollment the reference group has those not enrolled in college while those in non-arts enrollment (logit) model, the reference group has those enrolled in arts group. Thus the model results have to be interpreted carefully.

We expect the β2 to be to be insignificant in the college enrollment model and negatively significant in the non-arts stream model to possibly reflect no gender difference and higher male enrollment respectively based on the AISHE report findings. However, AISHE findings are based on the selection of individuals who are enrolled in college while the model here also includes those who are not enrolled. Thus we could expect lower female enrollment in both the models after controlling for other covariates given that in India women's participation in unpaid care work is considered more important than to participate in the labour market. However, if the findings of Klasen and Pieters (2015) for India that marriage prospects improve with education while there are fewer women in labour market at higher education levels were to hold then female enrollment in college may in fact be higher than males given that the latter may be taking up employment, particularly among the lower economic status households. Therefore, we are unable to predict a priori, the statistical significance and sign the female (β2) coefficient in the college enrollment model.

In the second variant of the model specification we now introduce the interaction terms of *Female* and *Social Networks* (after controlling for *Social Networks*) to test if access to networks improves participation for women and the model is specified as:

$$Y_i = \Lambda(\beta_1 + \beta_2 Female_i + \beta_3 Female_i * Social\_Network_i + \beta_4 Social\_Networks_i + \boldsymbol{X_i \gamma}) + \epsilon_i \quad (3)$$

The outcome variable (Y_i), *Female* and other control variables $\boldsymbol{X_i}$ are as defined earlier. *Social Network*$_i$ is binary variable with 0 for 'has no networks' and 1 for 'has access to some networks'. Having access to some networks refers to whether the individual's household knows anyone who is a teacher, a doctor, or a government servant. We expect the β_3 to be positive along with $\beta_2 Social\_Networks_i$ while β_2 could be negatively significant.

In the third and last variant of the model specification we introduce an additional interaction variable- gender of the individual with the gender of the contact person in the social network and the equation is as follows:

$$Y_i = \Lambda(\beta_1 + \beta_2 Female_i + \beta_3 Female_i * Social\_Network_i + \beta_4 Social\_Networks_i + \beta_5 Female_i * Female\_Network_i + \boldsymbol{X_i \gamma}) + \epsilon_i \quad (4)$$

Where $Female_i * Female\_Network_i$ equals 1 if the individual 'i' is female and the contact person in the network is also female. We expect this to capture the role model effect particularly if women coefficient is significant and negative and more so in the non-arts stream enrollment model. This is because if women in general are less likely to enroll due to biases in the system they live in, then a female role model could be a significant catalyst in realizing her aspirations after controlling for other covariates.

Binary choice models are non-linear models so the marginal effects are functions of the covariate values. However the logit estimates have the advantage that the odds ratio is a linear functions of the parameters and lends to an easier interpretation and hence the results are all reported as odds ratios (Long, 1997).

We now discuss in some detail the nature of social network variables and the covariates used as control variables in the analysis.

Data

This study is based on Indian Human Development Survey (IHDS-II) data for the year 2011-12 and for the year 2004-05. The IHDS is a large scale household survey conducted by the University of Maryland and NCAER. This is a unique dataset in the Indian context, as it is the only survey that collects nationwide household level panel data. Thus, households that were interviewed in 2005 were re-interviewed in 2012 and allowing to track the changes in social, economic and demographic aspects. There were some households that were lost due to 'attrition' (were not tracked in IHDS II), and these households were replaced with a new set of households. Thus, the total number of observations is different across the two years.

The sample here is restricted to individuals who were between 11 to 18 years of age in IHDS I (2005-06) and were thus 18 to 25 years of age in IHDS II (2011-12). We analyse the enrollment in IHDS-II, to ensure that all individuals are above 18 years of age (17 years is when Indian students typically appear for their HSE; however several students are also not on par and are a year behind). The upper limit is 25 as we also want to ensure that they weren't already going to college in IHDS-I so as to avoid any endogeneity. This sample also does not include individuals who were lost to attrition or were tracked but had migrated to a different household. Further, among the non-enrolled in the 18-25 year olds, the sample is restricted to individuals who have completed their 12th grade and have appeared for HSE[5]. Within these inclusion criteria, the econometric equations (1) and (3) are estimated with 11,138 sample observations.

As HSE completion is one of the main criteria for inclusion, we first discuss the nature of information available in the data for this variable. To account for one's motivation and ability to pursue higher education, the self-reported grade in HSE is used as a control variable. This is an ordinal variable with the grades reported as 'First Class', 'Second Class' or a 'Third Class' based on the cut-off scores decided by the examination board. There are several examination boards in India and the cut-off scores may marginally vary between them. In the absence of exact scores in the HSE exams and the fact that they are self-reported, some biases may be there in the actual rankings but should not be drastically different from the actual performance. This variable thus controls for an important individual characteristic of the eligibility to enroll into higher education and confounded with individual motivation. We expect that after controlling for other variables the higher the 'class' (rank) the better would be the chances of college and non-arts stream enrollment.

Household-level covariates are household mother's education, asset quartiles, income source, household size (number of members in the household) and social group. All these variables are constructed using the previous panel of 2005-06 (IHDS-I). Based on previous studies we expect mother's education rather than father's education to be strongly

[5] We restrict the sample to HSE completed 18-25 year old to ensure that we have a grade (or marks obtained in the HSE exam) for everybody in our sample

positively associated with the choice of daughter's enrollment in higher education[6]. This could be due to the direct influence as well as the indirect effect of a more empowered mother having better bargaining capability to overcome patriarchal norms and educate her daughter for a higher number of years and postpone her marriage. Mother's education refers to the number of years an individual's mother has been educated.

Current annual income, could be endogenous so we include log income from IHDS-I. Further, we consider a composite index for possession of durable goods to control for an additional variable for economic status of the household. This variable reflects the wealth status of the household which also includes the accumulative capacity of the household and also their credit worthiness, for households that may borrow to finance higher education. The probability density function of the scores from first principal component (estimated based on possession of several household durable goods and amenities) is categorised into four quartiles. The lowest quartile consisting of the bottom 25 percent of the households are relatively at the lowest end of the economic status and top 25 percent of the households are relatively the wealthiest and the middle two quartiles are at intermediate levels of economic status. We expect enrollment in higher education to be positively correlated with better economic status partly from the higher cost of education and hence affordability becomes a matter of concern and partly from the fact that the richer households can wait and invest in human capital of the younger adults and postpone their entry into employment. Along with economic status household's primary income source is controlled for based on whether the primary income source of the household is from agriculture, or non-agricultural wage labour, or salaried, or other sources. This is to account for the fact that certain

[6] We also expect that with arranged marriages being the norm in India, assortative mating would lead to a higher educated woman be married to a higher educated man and thus father's and mother's education would be highly correlated. The advantage of including mother's education is that both direct and indirect effects can be controlled for as mentioned further. Further, studies also show that once household's economic status is controlled for, education of the head of the households and will most likely be the father of the individual being analysed here so father's education has been excluded.

economic activities like agriculture and small business may need additional (family) labour that would preferably be unpaid in order that it does not affect the profits or turnover or high demand for seasonal labour. Young men and women may be employed in family's income augmenting activities and this may adversely affect the choice to enroll in higher education.

A larger household or a joint family could be more patriarchal and younger women in particular would be needed to assist in household chores and care of very young children and elderly. So we expect household size (the number of members who permanently stay in the household) to have a negative effect on enrollment.

In India, select caste groups, (in particular) scheduled castes (SC) and scheduled tribes (ST) and (to some extent) other backwards classes (OBCs) and some religious groups like the Muslims are not only deprived on monetary measures of poverty but also other dimension like health and education (OPHI, 2018). In order to redress the disadvantage, educational institutions have quotas with lower cutoffs in qualifying exams and fee concessions for the economically and socially disadvantaged. However, they still lag behind in educational attainment compared to their population share, while some improvements have been observed over the past decade and a half (Mahambre *et. al.* 2021 and Asher *et. al.*, 2021)[7]. Four dummy variables are included for SC, ST, OBC and upper caste Hindus (or *Brahmins*) with the reference category as other castes and a dummy variable for Muslims is included. Controlling for caste and religion is important in a model for higher education enrolment as gender effect could also be confounded with these variables. We expect these so called disadvantaged groups to have OR less than 1 or these categories may also be statistically insignificant once household's economic status and income source are controlled for.

[7] See https://theprint.in/opinion/education-levels-of-sc-st-obc-rising-a-new-study-looks-at-caste-gap-in-jobs-income-too/606200/

Southern states in India have improved their educational attainment and similarly, some states like Maharashtra and Delhi have a huge concentration of higher education institutions (Asher *et. al.*, 2021, AISHE, 2018). So we control for regional variations in access and attainment and area-level controls are captured by zone, area of residence and average education of the PSU. Area of residence refers to whether the respondent belongs to an urban area or a rural area. 'Zone' refers to the clustering of the different states into 6 zones where Jammu and Kashmir, Himachal Pradesh, Punjab, Chandigarh, Uttarakhand, Haryana and Delhi form the *North* zone; Uttar Pradesh, Jharkhand, Chhattisgarh and Madhya Pradesh form the *Central* zone; Rajasthan, Gujarat, daman and Diu, Dadra and Nagar Haveli and Maharashtra form the *Western* zone; Andhra Pradesh, Karnataka, Kerala, Tamil Nadu, Goa and Pondicherry form the *South* zone; Bihar, Sikkim, West Bengal and Orissa form the *Eastern* zone and Arunachal Pradesh, Mizoram, Manipur, Nagaland, Tripura, Meghalaya and Assam form the *North-Eastern* zone. Lastly, PSU Average Education refers to the average education level of the PSU (village or urban block in the IHDS) where the household is located. All these three variables constructed using IHDS-I, capture features of both supply and demand for education. Neighborhoods with more people who are better educated would have a demonstration effect and hence create a demand for it and in regions with large number of higher educational institutions will also attract more of eligible residents in the nearby region to enroll in it.

All these variables have been shown in previous literature as potential determinants of enrollment and controlling for it would take care of omitted variable bias if any on the coefficients of gender and networks variables. We also use sampling weights as provided in the survey data for all regression estimates discussed in the next section.

Main Findings

Table 3 reports the summary statistics of all the variables, for males and females separately. In this sample of 18-23 years olds, who have completed HSE we see that the females are more from urban areas and obtained grades that were on average higher than the males. Females also tend to come from richer households, belong to areas with higher education, on average have more highly educated mothers, and better socially networked than males. As female education in India is not held at the same bar as male education is it is hence observed that all these females who stayed in school till higher secondary belong to 'better-off' households, and thus are different from the males in the sample in terms of household and individual characteristics.

Table 3: Summary Statistics of Covariates

Variable and Source	**Males**				**Females**			
Age (in years)@	Count	Mean	Min	Max	Count	Mean	Min	Max
18	833	0.12	0	1	773	0.18	0	1
19	1057	0.15	0	1	796	0.18	0	1
20	986	0.14	0	1	779	0.18	0	1
21	903	0.13	0	1	528	0.12	0	1
22	895	0.13	0	1	504	0.12	0	1
23	690	0.10	0	1	353	0.08	0	1
24	688	0.10	0	1	315	0.07	0	1
25	802	0.12	0	1	280	0.06	0	1
Social Group@								
Upper Caste Hindus	1824	0.27	0	1	1243	0.29	0	1
OBC	2352	0.34	0	1	1375	0.32	0	1
SC/ST	1679	0.25	0	1	1044	0.24	0	1
Muslim	735	0.11	0	1	469	0.11	0	1
Others	264	0.04	0	1	197	0.05	0	1
Area@								
Rural	4277	0.62	0	1	2444	0.56	0	1
Urban	2577	0.38	0	1	1884	0.44	0	1
Household: Income Source@								
Agriculture	2602	0.38	0	1	1314	0.30	0	1
Non-Agricultural Wage	874	0.13	0	1	519	0.12	0	1
Others	1624	0.24	0	1	1218	0.28	0	1
Salaried	1754	0.26	0	1	1277	0.30	0	1
Grade obtained in HSC#								
First Class	1948	0.28	0	1	1596	0.37	0	1
Second Class	3914	0.57	0	1	2224	0.51	0	1
Third Class	992	0.14	0	1	508	0.12	0	1

(Contd …Table 3)

Variable and Source	Males				Females			
Age (in years)[@]	Count	Mean	Min	Max	Count	Mean	Min	Max
North Zone[@]	1583	0.23	0	1	1058	0.24	0	1
Central Zone	1224	0.18	0	1	805	0.19	0	1
West Zone	1521	0.22	0	1	829	0.19	0	1
South Zone	1548	0.23	0	1	988	0.23	0	1
East Zone	761	0.11	0	1	483	0.11	0	1
Northeast Zone	217	0.03	0	1	165	0.04	0	1
Household Assets[#]								
First Quartile	972	0.14	0	1	420	0.10	0	1
Second Quartile	1876	0.27	0	1	1034	0.24	0	1
Third Quartile	1949	0.28	0	1	1332	0.31	0	1
Fourth Quartile	2057	0.30	0	1	1542	0.36	0	1
PSU Average Education[#]	6854	7.99	0	15	4328	8.52	0	15
Income(Log) [#]	6835	10.51	0	14.58	4303	10.61	0	14.58
Household size[#]	43867	6.40	2	38	28290	6.54	2	33
Mother's education[#]	6854	4.01	0	16	4328	4.91	0	16
1 or more Networks[#]	4272	0.62	0	4	2936	0.68	0	4
Observations	6854				4328			

Source: Author's own estimations based on IHDS-1 (2004/05) and II (2011/12) data.
Notes: @ Refers to variables from IHDS-II and # are from IHDS-I

Table 4 shows the summary statistics of our two main dependent variables. If the individual continued to study post HSC either in college, or via distance education, or did a diploma course, they are counted within 'continues studying'. All students who switched to the labour market, or dropped out are counted in 'Dropped Out/Doing Nothing'. For all students who went to college, if they took any other stream apart from Arts, they were counted as enrolled in non-arts. This includes commerce, science, engineering, agriculture, home science and vocational studies. We see from the 'shares' column that female students were more likely to have continued into college post higher secondary, relative to male students. Here, we also see female students are enrolled in a much larger proportion in Arts compared to male students.

Table 4: Summary Statistics for College Enrollment

	Males		Females	
	Count	**Share**	**Count**	**Share**
Post Higher Secondary Dropped out/Doing Nothing	1059	0.15	498	0.12
Continued studying	5795	0.85	3830	0.88
Total	6854		4328	
Stream Chosen in College Arts	3130	0.54	2418	0.63
Non-Arts	2665	0.46	1412	0.37
Total	5795		3830	

Source: Same as Table 3.

Note: Non-arts includes commerce, science, engineering, agriculture, home science and vocational studies and the remaining courses are includes in 'Arts'.

Table 5 gives us the odds ratio of the logistic regression based on the regression results from equation (1). This regression reports estimated coefficients for the odds of enrollment using only the sex of the individual. Here enrollment into college is 1 for everybody who continued education Post-HSc and 0 for everyone who dropped out. Similarly, non-arts is 1 for everybody who enrolled into a non-arts stream and 0 for everybody enrolled into arts. *Female* is insignificant after household assets and household size are controlled for in the enrollment model and is a result different from Myroniuk *et. al.* The reason could be the differences in sample selection, the econometric model and the covariates used in this study. Since this sample includes only those who have finished higher secondary, it already consists of people with higher skills and motivation relative to those who might have dropped out and are thus not a part of the sample. As observed in Table 3, the females in our sample obtained slightly higher grades, came from wealthier families and lived in areas that had people with more education relative to the males in the sample. Within such a sample, we see that the coefficient for females enrolling into college is insignificant.

However, the more important finding is for the 'non-arts' regression in column 2. Here, female students have significantly lower odds of enrollment into a non-arts field relative to male students. Thus, even in this sample of students where female students are on an average more likely to enter college, controlling for everything else, they are still much less likely to enter into a field that is 'non-arts' in comparison to arts enrollment.

We also find that students who got First class were 5 times more likely to both enroll into non-arts as well as enroll into college relative to students who got Third Class. Similarly, even though the composition of the base category is different between these two models we also find that those who got second class were two times more likely to enroll into non-arts as well as college. Given that a higher share of students are enrolled in college (compared to the second model with non-arts alone), we expect each of the household asset category to be significant and positive in the college enrollment model with odds ratios increasing in magnitude as one moves up the asset quantile. On the other hand we expect that the upper quantile asset classes would be significant given lower share of students in non-arts enrollment and that non-arts science courses would involve higher fee that could be affordable by the richer sections. We find that the results are other way round and somewhat difficult to explain and may have to reexamine the role of economic variables allowing for a separation of enrollment between arts and non-arts from the non-enrolled ones as in a multinomial model or as a selection model with the first stage to model enrollment and second stage to model the stream of enrollment. Persons from households where the primary source of income is regular salary have higher odds of enrolling into college and into a non-arts stream, compared to any other primary source of income such as wage income or self-employment from either non-agriculture or agriculture.

Household size is significant in the non-arts model only with the odds of enrolling into non-arts is less than one compared to all others. Mother's education is significant for both the models and every additional year of mother's education leads to a one fold increase in the odds of enrollment into college or into non-arts stream.

Caste and religion variables are only significant in the non-arts model. SC/ST and Muslim students have lower odds of enrolling into a non-arts stream compared to students from other religion and not belonging to the four caste groups included in the model. Urban students also had significantly higher odds of enrolling into a non-arts stream. This may be because they have access to coaching classes and other resources that students residing in rural areas might lack. The average education of the area is also significant for both regressions; thus coming from an area with higher educated population positively increases the odds of enrollment into both college and a non- arts stream. Students living in the South had nearly 6 times higher odds of enrolling into a non-arts stream compared to students living in the North. This is a huge effect, and could be because of state level institutional and policy differences.

Table 5: Estimated Odds Ratios for Enrollment in College and into Non-Arts Stream

	Enrollment into College	Enrollment into Non-Arts
Female	1.137 (0.102)	0.450*** (0.0368)
HSE Rank: Third Class(base variable)		
First Class	5.682*** (0.759)	5.356*** (0.741)
Second Class	1.708*** (0.171)	2.251*** (0.314)
Income (ln)	0.990 (0.0279)	0.972 (0.222)
Number of Persons in the HH	1.009 (0.0140)	0.963*** (0.0113)
HH Assets Index Score: First Quantile- (base variable)		
Second Quantile-HH Assets	0.894 (0.106)	1.449*** (0.206)
Third Quantile-HH Assets	1.005 (0.133)	1.611*** (0.228)
Fourth Quantile-HH Assets	1.546*** (0.255)	2.172*** (0.328)
Mother's education (Completed Years)	1.105*** (0.0127)	1.044*** (0.009)
Caste and Religion: remaining religions and caste (base variable)		
Upper Caste Hindus	1.268 (0.278)	0.857 (0.130)
OBC	1.144 (0.251)	0.866 (0.131)
SC/ST	1.292 (0.297)	0.703**(0.120)
Muslim	0.900 (0.209)	0.504*** (0.0865)
Rural (base variable)		
Urban	0.753*** (0.0784)	1.380*** (0.135)

(Contd… Table 5)

	Enrollment into College	**Enrollment into Non-Arts**
Primary Source of Household Income: Agricultural wage(base variable)		
Non-Agricultural Wage	1.148 (0.171)	1.310 (0.218)
Others	0.966 (0.109)	1.138 (0.121)
Salaried	1.225^{*} (0.144)	1.295^{**} (0.137)
PSU Average Education	1.092^{***} (0.0237)	1.059^{***} (0.0228)
Geographical Zones: North(base variable)		
Central	1.579^{***} (0.213)	2.342^{***} (0.243)
	Enrollment into College	**Enrollment into Non-Arts**
West	0.882(0.113)	1.461^{***}(0.129)
South	0.662^{***}(0.0934)	10.30^{***}(1.357)
East	1.023(0.158)	1.326^{**}(0.170)
Northeast	0.801(0.175)	1.459^{**}(0.267)
Observations	11138	9584
Pseudo R^2	0.102	0.186

Source: Same as Table 3;

Note: (1) Standard errors in parentheses; (1) * p <0.10, ** p <0.05, *** p < 0.01

The main aim of this study is to understand the role of family networks after controlling for other factors on the odds of enrollment of both types. Table 6 below shows us the results of Equation (3) and the results for other covariates have been excluded from the table. Columns 1, 2 and 3 show the odds ratio for enrollment into college. However, all coefficients here are insignificant after using population weights. Columns 4, 5 and 6 shows us the same regression for enrollment into non-arts. Columns 3 and 6 show the results of equation 2. The odds ratio for *Female*Social Networks* is significant but less than 1. However, it still is greater than the odds ratio for Female in column 2. Thus, while the probability of enrollment of female with networks into a non-arts stream is still low, it is greater than the probability of a female with no networks (0.455>0.450). Comparing the odds of *Social Network* and *Female*Social Network* in column 3, we see that the odds of a male student with social networks enrolling into a non-arts stream is higher than the odds of a female student with networks, controlling for all else (1.299>0.455). Thus, some kind of an access to social networks largely increases odd of enrollment, but reduces these odds if the student is female.

Table 6: Estimated Odds Ratios for Enrollment with the Inclusion of Networks

	(1)	(2)	(3)	(4)	(5)	(6)
	Enrollment into College			**Enrollment into Non-Arts**		
Social Networks	1.034 (0.08)	1.011 (0.10)	0.981 (0.08)	0.953 (0.0720)	0.969 (0.0742)	1.299*** (0.107)
Female		1.095 (0.16)			0.450*** (0.0368)	
Female*Social Networks		1.069 (0.19)	1.169 (0.12)			0.455*** (0.0357)
Controls	Y	Y	Y	Y	Y	Y
Observations	11138	11138	11138	9584	9584	9584
Pseudo R^2	0.109	0.109	0.109	0.204	0.223	0.217

Source: Same as Table 3.
Note: Same as Table (5).

The IHDS data allows us another level of disaggregation. In case the household does have a network, the IHDS asks whether the person the family knows is female. We hypothesize that having female contact could have a significantly different effect, relative to having a male contact, especially for female students.

There could be three channels of this differential effect: First, a heightened role model effect. Female students who know female teachers, government servants, doctors or nurses could be inspired to follow into the same profession. There has been previous proof of such a channel such as in Beaman *et. al.* (2012), where using a natural experiment, they find that having good role models in leadership positions leads to higher aspirations and better educational outcomes for girls in India. Second, female students might find it easier to ask their female networks for help. Thus they might be getting more help and insight into the application process for colleges. This might push them into staying in college, or applying into fields they perceive as 'more rigorous' because they might be more confident and know someone else who did the same thing. Households could also be less apprehensive about their daughters pursuing a non-traditional field and this could be important in a country like India where households make a lot of decisions for the student. Third, is the labour market effect. Knowing that there are women working in these jobs might give female students confidence that their investment into education will not go to waste, and that the labour market does have a place for them. Primarily, Arts is perceived to be an easy and comfortable field to be in. However, having networks might convince students and parents that non-arts including STEM fields are not 'incompatible' to female students.

Previously, Social Networks was 0 if the individual had no networks and 1 if they had some networks. Now, we separate out these networks into the 3 types mentioned before: knowing someone in the medical field, or in the education sector, or a government servant. For simplicity we call these variables 'Knowing a Doctor', 'Knowing a Teacher' and 'Knowing a Government Servant'. Since we also know the whether these networks are male or female, we also have 'Knowing a Female Teacher', 'Knowing a Female Doctor' and 'Knowing a Female Government Servant'. Formally our specification is as given in equation (4) and we estimate three separate regressions for three types of network variables: 'Knowing a Doctor' or Knowing a Teacher', or 'Knowing a Government Servant'.

Table 7 reports only the results for the variables of interest defined as follows in the econometric equation. Knowing a Doctor is equal to 1 if the individual 'i' knows a doctor and 0 otherwise. Knowing a Female Doctor ($FemaleNetwork_i$ in equation (4)) is 1 if individual 'i' knows a female doctor. In Equation (4), the last term $Female_i * FemaleNetwork_i$ is the interaction between $Female_i$ and $FemaleNetwork_i$. Thus, Female Knowing a Female Doctor is equal to 1 if individual 'i' is a female who knows a female doctor. Here Y_i is Enrollment into college in columns 1, 2 and 3, and Enrollment into non-arts in columns 4, 5 and 6.

Columns 1, 2 and 3 produce no significant and intuitive results. This is in line with the previous specifications where our model was not a good predictor for college enrollment. Table 7, however reports some interesting and significant results. First, the odds ratio of 'Female' confirm the baseline, odds of female enrollment into non-arts streams is significantly lower than male odds. Second, the odds of 'Female Knowing a Female Teacher' are greater than 1. This means that for a female student, who personally knows a female teacher, the odds of enrollment into a non-arts stream are significantly higher than a student who doesn't have this network. This specific channel through a female teacher, could mean that female students do find it easier to ask help from and might even be additionally encouraged by these teachers. This is a striking result. We also note that males who know female doctors seem to also have higher odds of enrollment.

Table 7: Odds Ratio: Female Networks

	(1)	(2)	(3)	(4)	(5)	(6)
	Enrollment into College			Enrollment into non-arts		
Female	1.134 (0.105)	1.118 (0.103)	1.284* (0.177)	0.449*** (0.0382)	0.432*** (0.0373)	0.452*** (0.0423)
Knowing a Doctor	0.923 (0.0850)			0.912 (0.0689)		
Knowing a Female Doctor	0.989 (0.191)			1.424** (0.249)		
Female Knowing a Female Doctor	1.058 (0.326)			1.030 (0.286)		
Knowing a Teacher		1.053 (0.0859)			0.984 (0.0704)	
Knowing a Female Teacher		0.952 (0.185)			0.969 (0.162)	
Female Knowing a Female Teacher		1.481 (0.553)			1.759** (0.407)	
Knowing a Govt. Servant			1.302 (0.287)			0.729* (0.125)
Knowing a Female Govt. Servant			1.231 (0.418)			0.799 (0.187)
Female Knowing a Female Govt. Servant			0.363* (0.201)			0.943 (0.388)
Controls	Y	Y	Y	Y	Y	Y
Observations	11138	11138	5122	9584	9584	4536
Pseudo R^2	0.109	0.109	0.148	0.224	0.224	0.214

Source: Same as Table 3.

Note: Same as Table (5).

CONCLUSION

Educational achievements of the population happen gradually in a developing country. It starts with the target to achieve high literacy rate among young adults, then extends to 100 per cent enrolment in primary education among young children, and subsequently to 100 per cent enrolment in secondary education. In contrast to this, tertiary education is not considered compulsory among 25-64 year olds, with the completed rate ranging from about 20 per cent to 55 per cent across the developed world. It becomes a matter of individual's choice to pursue higher education and the stream of specialisation, like science, technology, humanities, liberal arts, business studies etc. As the private returns to higher education is substantially high in developing countries including India, the demand for education is expected to reach levels that are higher than the global average and at a faster rate than developed nations. For instance, at the beginning of the new millennium China's enrolment rate was about 8 percent and India's at 10 percent with China's increasing to 48 percent and India to 27 percent by 2016.

Human decisions are guided not only by financial and human capital, but also social capital. This study examined the role of family's social connections to a doctor or educationist or government official in gender parity in higher education as well as into the arts/science streams in India. The analysis being based on household and individual level data has been able to consider mostly demand side features that would determine access to higher education. Even after controlling for social and economic status family's network with the better educated makes a difference. Further, the gendered nature of this connection becomes more significant for women's choice to enroll in higher education. Human and financial capital is commonly understood to have a lot of influence on schooling choices. This study controls for several of these factors, as well as controls for individual ability and shows that females have significantly lower odds of enrollment into arts, even after controlling for grades, household income and assets, household size, caste, area and other such important variables. Access to some networks increases these odds, and knowing a female teacher turns these odds positive for females. These results are similar to that of Myroniuk *et. al.* (2017), who find that odds of enrollment to college favor women in the non-migrant sub sample. They hypothesize that this could be because the less academically inclined girls get self-selected out of the sample because of marriage, or a non-encouraging college environment.

Given that social connections seem to matter in access to higher education, this would limit the spread of access to higher education among young aspirants. College represents a huge jump in the process of education. It involves choosing a stream, and choosing an institution. It could often mean migration to a different city, moving out of the parent's house etc. Thus, it follows that parents who have access to information about this process, will feel more confident about it and will not hesitate as much as a completely clueless parent. Access to formal sector contacts could give such information to parents and provide support proves to be crucial at this stage. Supply side variables like access to transportation, presence of higher education institutions that admit only females and cost of education fellowships or scholarships could not be included in the analysis and may be important policy variables to improve educational mobility and equity.

Higher levels of education are expected to improve research and development capabilities and hence the economic growth rate of the region. In India, deep rooted social hierarchies result in disparity in access to higher education based on gender, region, caste and religion. The story of Anandibai Joshee is a moving example of someone who could disentangle herself from caste pride and prejudice, only after she left the country. Anandibai Joshee was the first Indian female physician. Married at a tender age, she fought against India's orthodox society and went on to pursue her higher studies in the US and came back as a certified doctor. In contrast, out of the first three women to ever work in Dr. C.V Raman's lab, none obtained a doctorate degree. Lalitha Doraiswamy got married to a physicist and stopped studying, Sunandi Bai committed suicide, and Anna Mani, despite having a fully written up dissertation, was not awarded a doctorate degree. All of this points to systemic discrimination and deep rooted biases. With returns to education having large gaps across different levels of education, this further entrenches economic inequality based on group identities. In this context the role of the three main key stakeholders: the state, market and the community (including the family) in providing access to affordable higher education becomes relevant.

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