

Gender Segregation in Education and Its Implications for Labour Market Outcomes: Evidence from India

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Abstract

This paper investigates gender-based segregation across different fields of study at the post-secondary level of schooling, and how that affects subsequent labour market outcomes of men and women. Using a nationally representative longitudinal data-set from India, we provide evidence that there is substantial intra-household gender disparity in the choice of study stream at the higher-secondary level of education. A household fixed effects regression shows that girls are 20 percentage points less likely than boys to study in technical streams, namely science and commerce, vis-à-vis arts or humanities. This gender disparity is not driven by gender specific differences in mathematical ability, as the gap remains large and significant even after controlling for individuals' past test scores. Our further analysis on working-age individuals suggests that technical stream choice at higher-secondary level significantly affects the gender gap in labour market outcomes in adult life, including labour force participation, nature of employment, and earnings. Thus our findings reveal how gender disparity in economic outcomes at a later stage in the life-course is affected by gendered trajectories set earlier in life, especially at the school level.

Keywords: Post-secondary education; STEM; Gender; Labour market; India

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1 Introduction

There are various forms of gender inequality observed in different parts of the world. In South Asia they have manifested throughout the life-course of individuals: sex imbalance at birth due to sex-selective abortions, unequal survival rates, differential human capital investments, discrimination in the labour market, and so on. The last few decades, however, have seen progress towards gender equality, most notably in education. While gender gap in enrollment rates at all levels of education has diminished, it has not translated into commensurate improvement in the labour market outcomes of women. The motivation behind this study stems from two recent and pressing issues of gender disparity in many developing countries, including India. First, female labour force participation which is viewed as one of the important indicators of inclusive development, has remained very low, stagnant and sometimes declining in India, despite the nation's rapid economic growth, female educational expansion, and fertility decline in the last two decades (Klasen and Pieters, 2015). Under-participation of women will pose a major hindrance for the country to properly utilize its demographic gift of having a high proportion of population in working-age. Second, occupational and sectoral segregation of employment by gender is remarkably persistent and is a key issue behind perpetuating female disadvantage, such as the gender pay gap in the labour market (Borrowman and Klasen, 2017). It is possible that the gender gap in economic participation in adult life is determined by gendered trajectories set earlier in life, especially at the school level. Therefore, this study seeks to link gender segregation prevailing in school education with gender disparity in labour market outcomes. Specifically, we identify the gender gap in stream choice at the post-secondary level of education. Further, we investigate how stream choice affects adult life employment and earnings of men and women.

There exists a considerable literature on post-secondary stream choice, its determinants and its implications (Fuller et al., 1982; Arcidiacono, 2004; Beffy et al., 2012). Many studies also recognize that educational segregation and occupational segregation go hand in hand. For instance, Schneeweis and Zweimüller (2012), in the context of Austria, argues that gender segregation in employment is explained by women's reluctance to choose technical occupations. However, they also show that the foundations for career choices are laid much earlier. Most of the studies in this literature are based on developed countries, with only a few exceptions such as Sookram and Strobl (2009) who investigate the relationship between educational and occupational segregation for Trinidad and Tobago. We seek to contribute to

this literature by investigating this issue in the Indian context. Over the last few decades, better access to schooling due to various government policies has resulted in narrowing of the gender gap in overall school enrollment and completion rates. However, gender disparity has manifested in terms of some more nuanced indicators, such as a female disadvantage in private school choice (Maitra et al., 2016; Sahoo, 2017). In this study we focus on the choice of study stream at the higher-secondary level of education. After secondary schooling which finishes at age 15, students are given the option of choosing from arts (humanities), commerce, science, engineering/vocational, and other streams for higher-secondary education (which lasts for another 2 years). This is a crucial juncture in their career because once they make the stream choice, most of them continue to pursue studying subjects in that particular stream subsequently in college and university.³ This choice also influences the nature of jobs that they may obtain in the future. We especially focus on the choice between technical (science/commerce/engineering/vocational) versus non-technical (arts/humanities) streams.⁴

We use a nationally representative household level panel data that track same households and individual members at two time points: 2005 and 2012. The novelty of this dataset is that it asks all individuals about their performance in the secondary school leaving certificate (SSLC) examination, and subsequently what stream they studied in higher-secondary level. Additionally, individuals aged 15-18 years (which is the official age for higher-secondary schooling) in 2012 can be matched with information on their prior skills in mathematics, reading and writing from an independent test that was conducted in the earlier round of survey in 2005. Thus, we have a unique setting to investigate higher-secondary stream choice of individuals after controlling for their past academic performances that serve as reasonable proxies of their cognitive ability.

³ Estimates from the data we use suggest that 93 (85) percent of students who are currently studying engineering (science) in college have studied a technical/STEM stream at the higher-secondary level. 85 percent of students who are studying arts in college have studied arts in higher-secondary as well.

⁴ Our categorization of subjects is closely related to STEM versus non-STEM subject groups. While traditionally STEM includes science, technology, engineering and mathematics, recently subjects such as accountancy or finance from the commerce stream are also considered close to STEM subjects as they involve mathematical tools. Another reason for considering commerce in the “technical stream” category is that many students in the commerce stream study mathematics and statistics. In later analysis, we also consider each subject separately in our analysis.

We estimate a household fixed effects model to take into account unobserved household-specific tastes and preferences. Our estimates show a significant intra-household gender disparity of around 20 percentage points in the choice of technical stream at the higher-secondary level among youth aged 15-18 years. The gender gap remains unchanged even after controlling for SSLC exam performance and lagged test scores from the previous survey, suggesting that it is not caused by any difference in cognitive ability between boys and girls. Moreover, we find that the gender gap is unrelated to household's affluence; rather, educational parity between parents and better access to technical education significantly reduce the gender gap.

While we find substantial gender segregation in school level stream choice, does this affect economic outcomes later in life? We reflect on this question by analyzing the relationship between higher-secondary stream choice and labour market outcomes of working-age individuals. Here also we include individual's performance in the SSLC exam as a proxy for innate ability – omission of which may result in biased estimates if individuals who choose technical stream are also better performers in the labour market because they have higher ability. We find that women have higher chances of participating in the labour force, getting salaried employment, choosing a male-dominated occupation, and having higher earnings when they have studied a technical stream in higher-secondary education. This particularly leads to a reduction of gender gap within household in terms of all these economic outcomes. Exploring this further, we find this relationship between education choice and labour market outcomes to be more prominent in urban areas. Also, among the technical subjects, science appears to have the most significant effect. We also show that the results remain robust to inclusion of additional control variables that partially capture women's personality traits.

Our study contributes to the literature in several ways. First, the importance of stream choice at the school level is an under-researched area especially in the context of developing countries. Second, in such settings it is rare to have information on school level stream choice, adult-life outcomes, and especially measures of ability on the same individuals. Having all three types of information from the same dataset allows us to investigate gender segregation in education as well as its connection to labour market outcomes, while mitigating the concern of omitted ability bias. Thus, our study is the first to credibly quantify the extent of gender gap in post-secondary stream choice in India. Further, it provides evidence that gender segregation in education determines occupational segregation and earnings gap in the labour market. This study is of significant policy relevance as it

emphasizes the need for promoting gender equality of opportunities at various stages of life. The issue of stream choice becomes increasingly important with rising enrollment rates of girls in secondary and post-secondary education. To achieve greater parity in labour market outcomes, policies need to focus on girls' access to technical education that can help them build human capital at par with boys. Such policies will be effective in enhancing women's participation in the labour market and in appropriate jobs, leading to efficient utilization of human resources and helping the economy derive greater returns from the "demographic dividend" associated with falling fertility and a low dependency ratio.

The rest of the paper is organized as follows. In section 2, we discuss the background and related literature. We explain the dataset and summary statistics in section 3. Section 4 contains the analysis of gender disparity in stream choice among individuals in higher-secondary age-group. This discussion includes both empirical model and results of the analysis. Section 5 shows how higher-secondary stream choice affects labour market outcomes of men and women. Section 6 concludes.

2 Background and Related Literature

In the last few decades, there has been considerable progress in terms of bridging the gender gap in educational attainment around the developing world. At the same time, trends in female labour force participation have been rather uneven with South Asia actually experiencing declining female labor force participation rates (Klasen, 2017). Moreover, a more nuanced analysis of this trend reveals that the nature of participation has not changed over time. Using data from 69 countries between 1980 and 2011, Borrowman and Klasen (2017) find that women have continued to be employed predominantly only in few sectors and occupations. Using data from India for approximately the same period, Duraisamy and Duraisamy (2014) find that occupational segregation has increased over time. These studies also find that this perpetuating trend in occupational and sectoral segregation is a major reason behind the existence of male-female earnings gap. Even in the context of USA, Blau and Kahn (2017) have found that gender differences in industry and occupation are more important determinants of gender pay gap than conventional measures of human capital.

On the education front, there has been a considerable rise in girls' school participation during the era when many countries implemented the "Education for All" program. In India, while there was a substantial gender gap in school enrollment in the mid 1980s and 1990s, it has

practically disappeared in recent times. It is particularly noteworthy that this trend is true even at the secondary and higher-secondary levels of education, suggesting that adolescent girls are now as likely as boys to attend school at this level. The choice of field of study at the higher-secondary level is an important decision in an individual's career because it is the first step towards further specialization at the subsequent levels of education and also for labour market outcomes such as occupational choice. There are various studies, mostly on developed countries, which analyze the determinants of post-secondary field of study choice. The literature also highlights that educational choices at this level and labour market outcomes are closely linked. On one hand, the choice of a particular field of study is found to be affected by the expected future earnings from different fields (Boudarbat, 2008; Beffy et al. 2012). On the other hand, such educational choices also cause much of the variation in earnings later in life (Dustmann, 2004; Joensen and Nielsen, 2009).

Focusing on gender, studies have commonly found the existence of gender disparity in the choice of study-streams – girls are especially under-represented in science, technology, engineering and mathematics (STEM) at the post-secondary and tertiary levels of education almost all over the world (Hill et al., 2010; Flabbi, 2011). The World Development Report 2012 points out that “the seeds of segregation are planted early” and “gender differences in education trajectories shape employment segregation” (World Bank, 2012, p. 216). Various studies have sought to analyze the extent and causes of gender streaming in education and its relation to occupational segregation. Decomposing the overall gender segregation in the Flemish labour market, Van Puyenbroeck et al. (2012) find that the choice of study field has a larger effect on overall segregation than sectoral choice which itself is partly explained by educational choice. In the context of Bulgaria, Bieri et al. (2016) documents that stream choice at the tertiary level affects men's but not women's choice of male versus female-dominated occupation. Using a sample of OECD countries, Flabbi (2011) finds that gender is a significant determinant of the chosen field of study, that females are less likely than men to choose science and social sciences, and more likely to choose humanities. Further, this choice significantly explains the gender-wage gap and the relationship between field of study and labour market outcomes varies between men and women. This link was also explored in some earlier studies using data from the USA. Daymond and Andrisani (1984) found that differences in college major choice by men and women accounted for a large part of the gender wage gap in the 1970s. Other studies also suggested that increasing the proportion of

women in male-dominated majors would lead to a substantial decline in the gender wage gap (Eide, 1994).

Since girls are less likely to choose STEM subjects, one potential reason that has been explored in the literature is whether boys have a comparative advantage in mathematics. Various studies have found evidence which contradicts this hypothesis. For instance, Friedman-Sokuler and Justman (2016) find in Israel that gendered choices remain unperturbed even after conditioning on differences in perceived mathematical ability captured by prior achievement. Similar conclusions have been drawn in the context of USA by several other studies using various measures of cognitive ability such as high school academic preparation and Scholastic Aptitude Test scores (Turner and Bowen, 1999; Dickson, 2010; Riegle-Crumb et al., 2012). The received wisdom from the literature is that inherent gender difference in cognitive ability is almost non-existent; rather, other societal, psychosocial and preference related factors play a larger role in explaining the under-representation of women in math-intensive STEM subjects (Antecol and Cobb-Clark, 2013; Zafar, 2013; Buser et al., 2014; Kahn and Ginther, 2017).

Most of the evidence on field of study choice is limited to advanced economies. It is perhaps not surprising that very few studies have analyzed this issue in the context of underdeveloped countries which, until recent times, have struggled even to raise enrollment rates. However, with a substantial increase in school participation, now the focus is shifting from quantity to quality aspects of education. Stream choice at the school level captures an important aspect of the quality of education, as it potentially affects future employability and earnings. Goldin et al. (2006) show that between the 1970s and 1990s, choice of math and science in high school significantly contributed to the reversal of gender gap in college completion rates in the USA. Therefore, to ensure that the progress in girls' school enrollment sustains through tertiary education in India, it is imperative to analyze stream choice in this context.

3 Data and Descriptive Analysis

We use a nationally representative two period longitudinal dataset called the India Human Development Survey (IHDS).⁵ The first round of data was collected in 2004-05 on 41,554

⁵ IHDS was carried out jointly by the University of Maryland and the National Council of Applied Economic Research, New Delhi. The dataset is publicly available. More details can be found here: <https://ihds.umd.edu/>

households in 1503 villages and 971 urban neighborhoods across India. In 2011-12, the second round of survey re-interviewed 83 percent of the same households and for those households which could not be tracked, a replacement sample was used. Thus, the second round of survey covered 42,152 households across India. For the purpose of brevity we will refer to the first round as 2005 data and the second round as 2012 data. IHDS is a multi-topic survey consisting of detailed information at the levels of individuals, households, and communities. The analysis in this paper mainly uses the sample from the 2012 survey, and uses the 2005 survey to account for past characteristics of the same individuals.

At first, we seek to explore whether there is a gender bias within households in the choice of study stream at the higher-secondary level. In India, the official school entry age is 6 years, and the (lower) secondary level ends at the completion of 10 years of schooling. In the IHDS sample, the enrollment rate of children who are in the secondary age-group (14-15 years) is 87 percent and the gender gap in enrollment rate is only 2 percentage points. The succeeding level after secondary consists of two years of schooling, called “higher-secondary” (or senior-secondary, or upper-secondary) is the level we want to consider here. Therefore, we concentrate on the sample of individuals who are in the age-group of 15-18 corresponding to the higher-secondary level of education.⁶ There are 14,845 children in this age-group. Information on stream choice at the higher-secondary level is available only for those individuals who have passed secondary level and enrolled in the subsequent level of education. The secondary pass rate for our sample is around 40 percent, 39.4 percent for males and 40.6 percent for females. A t-test reveals that the gender difference in the secondary pass rate is statistically not significant. After dropping observations with missing values, the final sample of analysis consists of 5213 children.

The first step towards specialization begins at the higher-secondary level of education where students have to choose a stream mainly from the following options: arts, commerce, science, engineering/vocational, and others (home science, craft, design, etc.). Estimates from IHDS data show that more than 50 percent of individuals of all age groups who have studied at this level have chosen the arts stream. The next popular streams are commerce and science,

⁶ Strictly speaking, the age band corresponding to higher-secondary level should be 16-17 years. However, we include one year below and above to allow for the possibility that some children may finish secondary level earlier, and some children later. The enrollment rate among children in 16-17 year age is 74 percent, however, many of them are yet to complete secondary level schooling.

followed by engineering/vocational and others which are chosen by very few. Females are always more likely than males to study arts, and less likely to study science, commerce, and engineering/vocational. Consistent with the existing studies on other countries, this crude measure of gender gap in stream choice suggests that girls are under-represented in the STEM subjects also in India.

To explore the link between post-secondary stream choice and subsequent labour market outcomes, we consider adult individuals aged 25-60 years. After dropping missing observations on the relevant variables, we have a sample of 80,302 individuals who are included in the analysis of labour market outcomes. The secondary pass rate in the adult sample is 21 percent, as secondary school participation was much lower in the earlier decades. Among those who have passed secondary education, 39 percent men and 28 percent women opted for technical streams at the higher-secondary level, the remaining mostly studied arts or humanities. The overall labour force participation rate of 60 percent masks a huge gender gap, as only 26 percent women against 96 percent men have participated in the labour force. Among those who participate as salaried employment and casual wage labour, we have information on their annual earnings and the number of hours they worked in the last year. Figure 1 shows the kernel density estimates of log of annual and hourly earnings of adult individuals based on what they studied at the higher-secondary level and gender. The figure indicates that earnings of those who studied a technical stream clearly dominate the earnings of those who studied a non-technical stream. We also find that there is a substantial gender gap in the whole distribution of earnings. In a later part of our study, we investigate whether higher-secondary stream choice can be connected to these observed differences in labour market outcomes.

4 Analysis of Gender Gap in Technical Stream Choice

4.1 Empirical Model to Identify Intra-household Gender Gap in Stream Choice

Our first objective is to identify if there is an intra-household gender disparity in the choice of technical stream versus non-technical stream (arts / humanities). We use the following econometric model:

$$Prob(Techedu_{ih} = 1) = \alpha + \beta Female_{ih} + \gamma X_{ih} + \theta Ability_{ih} + \phi_h + \varepsilon_{ih} \quad (1)$$

We estimate a linear probability model where the dependent variable is a binary indicator of whether an individual aged between 15 and 18 years, corresponding to the higher-secondary level of education, has chosen to study in technical stream ($Techedu = 1$) or arts/humanities ($Techedu = 0$). The subscript i denotes individual and h denotes household. The main explanatory variable is gender reflected by a dummy variable ($Female$) to denote whether the individual is female. In addition, we control for age, birth order, number of siblings, mother's years of education, and father's years of education.

There are various household level factors, including unobserved taste and preference towards different types of education, that potentially affect the stream choice. We control for household level heterogeneity by including household fixed effects (ϕ_h) in the regression.⁷ This enables us to compare between boys and girls in the same household to identify the gender gap. This is especially important in the context of India where household's unobserved preferences are correlated with various forms of gender inequality. Often female children are more likely to be found in larger families because fertility decisions are endogenously determined wherein parents keep having children until they have at least one boy (Yamaguchi, 1989; Clark, 2000; Basu and Jong, 2010). If technical education needs higher investments, then comparisons across households may artificially show a gender gap because girls belong to larger families where investment in the human capital of each child is less. Due to these reasons, existing studies that investigate gender discrimination in educational investments advocate using household fixed effects (Jensen, 2002; Kingdon, 2005; Sahoo, 2017). Using fixed effects also imply that the effects of various observable household characteristics are subsumed by these fixed effects.

Within households, gender difference in the choice of technical education may be driven by the possibility that girls have lower cognitive ability than boys, especially in terms of their performance in mathematics which is an essential subject for technical education. There is an expansive literature that looks at gender gap in mathematics achievement and concludes that most of the observed gap is explained by background factors (Benbow and Stanley, 1980; Nollenberger et al, 2016). In the Indian case, because of systematic and continual under-

⁷ Note that inclusion of household fixed effects implies that only those households with at least two individuals contribute to identification in this regression. In comparison with the overall sample, the number of such households, i.e. with at least two individuals in age-group 15–18 years, is much lower at 1085. Therefore, we present results both with and without household fixed effects.

investment on girls' human capital from early childhood, when girls reach the level of higher-secondary education, they may be lagging behind boys in terms of mathematical ability. A novel feature of our data allows us to account for this problem. In the 2005 IHDS round, children who were in 8-11 years age-group were given cognitive tests on mathematics, reading, and writing ability. Incidentally, in the 2012 survey, these children are in the right age-group corresponding to higher-secondary level, and considered in the regression. Therefore, we are able to control for their past cognitive ability by including their performance in these tests.⁸

In addition to accounting for past test scores, children's performance in the secondary level board examination is potentially an important predictor of stream choice at the higher-secondary level. In India, there is a standardized examination conducted by the education board (state or national level) to which each school belongs. Every student has to pass this examination and obtain the secondary school leaving certificate (SSLC) to be able to continue higher-secondary levels of education. The results of this examination are typically categorized into divisions 1, 2, and 3, in the declining order of the quality of grade obtained by a child. In addition to prior test scores, we also use this SSLC performance indicator to further control for cognitive ability of the child. Therefore, we control for achievement scores collected by two independent tests: one was conducted by IHDS enumerators in 2005 survey, and the other by the SSLC board. Hence we believe that our regression adequately captures the differences in abilities of children and identifies the gender gap in stream choice.

A potential concern that remains is the fact that stream choice is defined only for those individuals who have passed the secondary level and enrolled in higher-secondary level. Summary statistics presented in Table 1 shows that 40 percent of children passed secondary level. It is likely that these children are systematically different from those who have an education below the secondary level. However, disaggregating this pass rate by boys and

⁸ There is a substantial reduction in sample size by about 50 percent when we control for past test scores from the previous round of survey. This is due to many missing values in the variables capturing past test scores (as evident from Table 1 presenting summary statistics). Some individuals (about 11 percent of the sample) could not be found in the 2012 survey, and some other individuals may have misreported their age in the previous survey, leading to missing values in test scores for this age-group. To show that our estimates are not driven by variation in sample size, we present multiple specifications where we add covariates gradually.

girls, we find that there is no gender gap in secondary level pass rate. To further investigate this matter, we run a regression similar to Equation (1) but with the dependent variable being a binary indicator of whether a child has passed the secondary level (hence eligible for higher-secondary stream choice). The result of this regression shows that the coefficient of gender is almost always insignificant and the magnitude is almost zero. Therefore, it suggests that the probability of selecting into the sample of our main regression (stream choice) does not vary by gender. Hence this is unlikely to confound the effect of gender in the regression of technical stream choice.

4.2 Results on Gender Gap in Stream Choice

First we focus on intra-household gender differences in the choice of technical stream at the post-secondary level. The results from estimating Equation (1) are given in Table 2. The first column presents a model that includes only some basic individual level control variables, such as age, birth order, and parental education. Household fixed effects are included in the subsequent models. We add the control variables in sequence to check if the coefficient of gender is sensitive to varying specification. Column 2 considers the SSLC exam performance as past ability control, while column 3 accounts for the prior mathematics score from the earlier survey round. The final column presents the full model including all measures of cognitive ability.

In all of the regressions, there is a statistically significant female disadvantage in the choice of technical stream. Girls are approximately 20 percentage points less likely than boys to study a technical stream vis-à-vis humanities. Among all boys and girls, 50 percent are enrolled in the technical stream. This implies a gender gap of a magnitude of 40 percent which is very substantial.

Turning to the other variables, education of both parents has a positive effect, with the effect of mother's education being substantially larger. But, unsurprisingly, it becomes imprecise once household fixed effects are included as little variation is left to identify effects. As expected we find that students who score better in the secondary level board examination (SSLC) are more likely to study a technical stream at the higher-secondary level. Among the variables capturing the past test scores, mathematics has a significant effect. Considering that these independent tests were designed to assess very basic level of knowledge, it is not surprising that only the highest level of difficulty in mathematics, i.e. division, comes out to

be the only significant predictor of choosing the technical stream. The effect of mathematical ability remains significant even when all the controls are included in the final model.⁹ However, the gender gap also remains significant and the effect size is almost unperturbed even after taking into account the variation in cognitive abilities. This finding strongly indicates that the gender gap in stream choice is not driven by the intrinsic ability of students.

Heterogeneity in gender gap

To explore what drives the gender gap in stream choice, we include interaction terms of gender and other explanatory factors in the regression. To explore the heterogeneity in the effect of gender, we particularly focus on three factors: household affluence, parental educational parity, and access to technical education. It is likely that studying a technical stream involves higher cost (Chandrasekhar et al., 2016); therefore, wealthier households may have better capability to enroll children in technical education. As revealed in Table 3, there is no significant effect of household income on gender gap in stream choice, although households with higher income are more likely to enroll boys in technical stream. We next consider parental educational parity, as defined by the difference in years of education between mother and father. Since mothers usually have lower levels of education than fathers, a greater parity implied by relatively higher education of mother may reduce gender disparity in their children's education as well. We find that this is indeed the case (Table 3). On average, a mother has 1.7 years lesser education than father; if this figure improves and there is equality in educational attainment between the parents, then it reduces the gender gap in technical stream choice of their children by 3 percentage points.

Another pertinent question from the supply side of education is whether gender disparity reduces when technical education is made more accessible. We interact with gender a variable that measures the total number of science and technical colleges in the district at the time when the choice of technical stream was made.¹⁰ The results show that districts with higher number of colleges that provide science or technical education not only attract more students to study technical stream, but also it helps reduce the gender gap in stream choice. A standard

⁹ We do not find any significant effect of other measures of cognitive ability, i.e. reading and writing scores, on stream choice. This result is consistent with Arcidiacono (2004) who found math ability to be more important than verbal ability in explaining sorting into particular majors in the context of USA.

¹⁰ We use All India Survey of Higher Education data to construct this variable.

deviation increase in the number of science/technical colleges per million population in the district is associated with a reduction of 13.5 percentage points in the gender gap in higher-secondary stream choice.

Gender gap in the choice of individual streams

As mentioned before, technical stream includes STEM and commerce streams, while non-technical stream represents arts or humanities. To understand the gender gap in each stream separately, we estimate a multinomial logit model using the same explanatory variables as described in Equation (1). Since one cannot include fixed effects directly in such a non-linear model, therefore we express the household fixed effects as linear functions of the household specific averages of the individual level explanatory variables, as suggested by Mundlak (1978). Results (provided in the appendix) show that girls are 22 percentage points more likely than boys to choose arts than other subjects. The gender gap favoring boys is highest for science (9.5 percentage points) followed by commerce (8.8 percentage points). It is not significant in the choice of engineering/vocational or other streams, which have very low overall enrollment rates – only about 5 percent individuals study there.

5 Relationship Between Stream Choice and Labour Market Outcomes

5.1 Empirical Model for Labour Market Outcomes

For this analysis we consider all individuals in the age-group of 25-60 years. The dependent variable Y_{ih} is a specific measure of labour market outcome of individual i from household h . Our model for estimation is given below:

$$\begin{aligned}
 Y_{ih} = & \delta + \eta \text{Female}_{ih} + \lambda (\text{Female}_{ih} \times \text{Sec}_{ih} \times \text{Techedu}_{ih}) + \psi (\text{Female}_{ih} \times \text{Sec}_{ih}) \\
 & + \pi (\text{Sec}_{ih} \times \text{Techedu}_{ih}) + \sum_k \tau_k \text{Eduyear}_{ihk} + \rho \text{Ability}_{ih} + \zeta X_{ih} + \sigma_h \quad (2) \\
 & + \epsilon_{ih}
 \end{aligned}$$

Among the main explanatory variables, we have gender of the individual (Female_{ih}), an indicator for whether the individual has passed secondary level of education (Sec_{ih}), and whether the individual studied in a technical stream (Techedu_{ih}) in the higher-secondary level. Note that stream choice is applicable only for individuals who have passed secondary level, hence we include Techedu_{ih} interacted with Sec_{ih} . Therefore, π captures the effect of

technical stream choice for men given that he has at least secondary education degree. Similarly, λ gives us the additional effect of technical stream choice for females given that her education level is at least secondary. It is possible that having a secondary level education itself has a differential effect on earnings by gender. To ensure that the effect of technical stream choice is not confounded by the effect of secondary level education, we also interact the gender dummy with the secondary-pass dummy. This helps us to identify any differential effect of stream choice over and above any effect of secondary level of education. The variable Sec_{ih} does not appear separately in the equation because it is subsumed in the set of dummy variables indicating years of education ($Eduyear_{ihk}$).

This analysis essentially is very similar to estimation of returns to education where the usual omitted ability bias is a concern. Individuals who choose a technical stream in their higher-secondary education may have better ability because of which they may also perform better in the labour market later in life. If this is true, then the effect of technical stream choice may be overestimated. The data on secondary school leaving certificate (SSLC) examination results are available for all individuals including the adult sample. Therefore, we include this variable as a proxy for cognitive ability in this regression.¹¹ Since the results of the SSLC examination are available only for those who have passed this level, therefore this variable is interacted with the secondary pass dummy. Thus, in essence, ability is controlled for those individuals who have passed secondary level.

We include household fixed effects (σ_h) in the regression. Therefore, the coefficients of gender and its associated interaction terms measure gender disparity in economic outcomes within households. The importance of using a household fixed effects model lies in the fact that much of the variation in female labour force participation is caused by household level determinants in India (Sarkar et al., 2017). Unobservable preferences such as family status concerns determine what kind of employment is deemed fit for women. For instance, households which prefer women to be homemakers may be less likely to enroll girls in professionally oriented technical courses. Besides, in a patrilocal residence system, girls with technical education may have lower probability of marrying into a family that has views against women's involvement in labour market. Therefore, it is important to control for household level heterogeneity that determine whether a woman has technical education as

¹¹ Azam et al. (2013) use a similar strategy to examine returns to English language skills in India using the first round of IHDS data.

well as her employment outcome. Fixed effects would absorb all observable and unobservable household specific factors that may be relevant in this context. Additionally, we control for individual level factors (X_{ih}) such as marital status and relationship to head of the household, which are important determinants of labour market participation, especially for women.

The model allows us to test two relevant hypotheses. First, whether women who study technical stream at the higher-secondary level have better labour market outcomes, i.e.,

$$\begin{aligned} E(Y | Female = 1, Sec = 1, Techedu = 1) - E(Y | Female = 1, Sec = 1, Techedu = 0) \\ = \lambda + \pi > 0 \end{aligned}$$

And second, whether women are able to reap greater benefits from studying technical stream than men, thus technical stream choice reducing gender gap in economic outcomes, i.e.,

$$\begin{aligned} [E(Y | Female = 1, Sec = 1, Techedu = 1) - E(Y | Female = 1, Sec = 1, Techedu = 0)] \\ - [E(Y | Female = 0, Sec = 1, Techedu = 1) - E(Y | Female = 0, Sec = 1, Techedu = 0)] \\ = \lambda > 0 \end{aligned}$$

In the tables containing the results of our analysis, we present the main coefficients, and include $(\lambda + \pi)$. We also estimate Equation (2) by replacing *Techedu* with individual subjects to explore the effect of different subjects separately.

5.2 Results: Effect of Stream Choice on Adult Life Outcomes

Results of estimating Equation (2) are presented for the overall sample, and also separately for a rural and urban sample acknowledging the possibility that the labour market may be structurally different between rural and urban areas. We discuss the effect on different outcomes as follows.

Labour force participation

Table 4 presents the results of the regression where the outcome variable is whether an individual participates in the labour force, according to the principal activity status during the last one year from the date of survey. Since men's labour force participation is almost universal (96 percent), therefore having a technical degree may not make any difference for them. However, women's labour force participation, as corroborated by the recent literature, is very low at 26 percent in our sample. The regression shows that the female dummy is large, negative, and highly significant; interestingly, it is even slightly larger for those women with a

secondary pass, in line with the literature showing a u-shape effect of education on female participation (Klasen and Pieters, 2015; Sarkar et al., 2017). One of the reasons behind low FLFP is that not all jobs are considered suitable for women to participate, which is partly due to social stigma and family status concerns (Klasen and Pieters, 2015). Having a technical education may enable a woman to gain access to better-quality jobs – which may encourage her to take up employment. Without a technical education, she may only be able to get a lower-quality job and hence not participate at all, as returns from household production or status concerns may prevent her from taking up that job. However, these mechanisms are unlikely to apply for men, as almost all of them participate in the labour market. It is therefore possible that women benefit more from studying in a technical stream than men, resulting in a reduction of gender gap in labour force participation.

Let's first consider the total effect on women as captured by the term $(\lambda + \pi)$, which is statistically significant and positive in the overall, rural and urban samples. The probability that a woman will participate in the labour market increases by around 9 percentage points when she has studied in a technical stream as compared to arts or humanities at higher-secondary level. As expected, there is no effect of technical stream choice on men's participation. Hence, the coefficient λ that captures the differential effect on women versus men, is also significant and positive. This suggests that among those who have studied at the higher-secondary level, the choice of technical stream significantly reduces the gender gap in labour force participation. Decomposing the effect of technical stream into various individual streams, we find that the effect is mainly driven by science and engineering/vocational subjects.¹²

To explore any potential effect on the nature of employment, we use information on the type of labour market engagement of individuals, namely salaried employment, casual wage labour, family business, family farm and animal rearing.¹³ In both rural and urban samples, we find that women with technical education have higher probability of getting a salaried job which is by far the most remunerative employment. The effect on men is null. Results also show that these women are less likely to engage in family farm and animal rearing activities.

¹² Among other variables, having scored in the first division in the SSLC exam has a significant positive effect on labour force participation especially in urban area.

¹³ These results are presented in the appendix.

Further, we categorize occupations as male or female dominated based on the share of men employed in each occupation. Occupations which have higher share of male employees also offer higher income. We find that women with technical education are more likely to be employed in a male dominated occupation, especially in urban areas. This finding motivates us to examine the effect on earnings.

Earnings

The final labour market outcome we consider is the annual earnings of all working individuals. We estimate the regression with logarithm of annual earnings for all workers as a dependent variable. We also consider annual work intensity and hourly earnings in the later part of this analysis. Individual specific earnings are recorded only for those engaged in casual wage or salaried employment. Due to this, we tackle the problem of sample selection by following Heckman's two-step selection correction model. In the first step, a probit equation modeling participation is estimated, and the selection correction term (Inverse Mills ratio) is calculated, which is then included as an additional control in the main earnings equation.¹⁴ The standard errors are bootstrapped to avoid the problem of generated regressor.

Table 5 presents results of estimation without selection correction in columns 1–3, and with selection correction in columns 4–6. The Inverse Mills ratio is statistically significant in the selection-correction model for the overall, rural and urban samples. Without selection correction, the main coefficients are slightly underestimated. We find that the female dummy which reflects gender gap in earnings for those who have education below the secondary level is always significantly negative, revealing the large gender gap in earnings that prevails in the labour market. The interaction between female and secondary pass is positive and significant, suggesting that having a secondary level education helps women more than men in terms of earnings gain. Furthermore, we find that the interaction between female, secondary pass, and technical stream is positive and significant in the urban sample. This implies that among those

¹⁴ For ease of identification, the participation equation should contain some extra variable(s) not included in the main earnings equation. We follow the existing literature and use household size as an identifying variable because it is likely to affect income of an individual only through the incentives to participate (Nielsen and Westergård-Nielsen, 2001; Doud, 2005; Agrawal and Agrawal, 2018). We also include an interaction of female dummy with household size to allow the effect to vary by gender. Household size significantly increases participation of males, but there is no differential effect on females.

individuals who have at least secondary level of education, having studied in a technical stream rather than arts reduces the gender gap in earnings by 28.2 percentage points. The reduction in gender gap accrues from a significant positive effect of technical education on women's earnings, while the same effect on men is insignificant.¹⁵

Additional analysis (see appendix) shows that the effect is entirely driven by science. In fact, studying in the science stream, as compared to arts, reduces the gender gap in earnings both in the overall and the urban samples. Studying engineering/vocational has a positive effect on the earnings of only men. For both men and women, stream choice does not affect earnings in rural areas. Cognitive ability plays a role: those who have passed in the first or second division in secondary school leaving exam have significantly higher earnings as compared to those who have passed in the third division. However, the effect of cognitive ability is significant only in the urban areas, suggesting that earning opportunities in rural and urban areas are structurally different.

Technical education may boost up female labour force participation not only at the extensive margin, but also at the intensive margin. If employed individuals work for more number of days, that may lead to higher annual earnings. On the other hand, annual earnings may increase due to a rise in the wage rate which may reflect participation in better quality jobs. To separate out these two effects, we consider two additional outcome variables: individual's work intensity measured by the total number of hours worked in the last year, and hourly earnings. We find that women who have studied in a technical stream have higher work-intensity, and this effect is stronger in the urban sample. There is also a positive and significant effect of technical education on hourly earnings. This effect is found only in the urban areas, which is again consistent with our previous results. These findings imply that the pathway through which annual earnings rise when women have technical education, is partly increased work intensity and partly higher hourly income.¹⁶

¹⁵ Note that without household fixed effects, men with technical education earn more, suggesting that this premium is due to unobserved heterogeneity at the household level.

¹⁶ This explanation is also supported by an additional analysis, where we include work intensity as a control variable in the regression considering annual earnings (results not presented). The effect of technical education remains significant and positive for the urban sample, however, the magnitude diminishes.

5.3 Interpretation and Robustness of Results

A pertinent question is whether the estimated relationship between stream choice and labour market outcomes captures the causal effect of technical education. If there are unobserved individual specific characteristics that propel women to self-select into technical education, and also drive their labour market performance, then the estimated effect is not causal. The existing literature on the confounding effect of omitted ability emphasizes that it causes an upward bias in the estimate. To mitigate this issue we use SSLC examination performance as a proxy for ability. Although it is a meaningful measure of ability, yet it may not comprise all the dimensions of ability, especially those related to non-cognitive skills. A growing literature shows that non-cognitive or behavioral traits are important determinant of both stream choice and labour market outcomes. Existing studies such as Buser et al. (2014) emphasize that gender differences in competitiveness substantially explain why boys choose more math- and science-intensive streams. Most of these studies are based on laboratory experiments from advanced economies. Since we deal with observational data that do not have any direct measure of non-cognitive skills, therefore we are unable to examine whether the gender gap in stream choice is caused by any gender difference in non-cognitive characteristics.

What is also critical is the implication of omitted behavioral factors in the regression that links stream choice to labour market outcomes. Insofar as these behavioral aspects are not captured by the included proxy for ability or the household fixed effects, we cannot rule out the possibility that women who break the gender barrier and indeed choose the technical stream have a particularly strong personality and hence achieve better economic outcomes later in life. We seek to address this by including a few additional control variables that partially capture personality traits of women. For a subset of women in the sample, IHDS collected additional information on their intra-household decision making and participation in various social and political activities in the community.¹⁷ This subset consists of 74 percent of the women who are included in our sample of adult individuals. Using principal component analysis on individual variables, we construct two indices. The first index reflects to what extent the woman participates in decision making about day-to-day matters in the

¹⁷ The eligible women for additional information in the 2012 survey are those who were present in the 2005 survey, and an ever-married woman aged 15-49 years.

household.¹⁸ The second index captures her involvement in community organizations: membership in women's group, self-help or microcredit group, any political organization, and participation in public meetings. Johnston et al. (2016) show that there is a strong connection between non-cognitive skills and intra-household decision making of individuals. Therefore, these indices can be considered as a proxy of women's personality traits. We include them as additional controls in our regression. Women for whom we do not have this information are dropped from the sample for this robustness analysis. Note that we do not have information on men's personality; therefore these variables are included as an interaction with the female dummy.¹⁹ The indices of decision making as well as social and political participation are found to have a statistically significant and positive effect on the outcome. However, the effect of technical stream choice still remains significant and there is a negligible change in its magnitude. Therefore, it seems that the relationship is unlikely to be mostly confounded by personality traits of individuals.

6 Conclusion

In this study, we provide the first quantitative estimate of the extent of gender segregation in post-secondary stream choice, and its potential impact on gender inequality prevailing in the labour market of India. We show that within-households, girls are 20 percentage points less likely than boys to choose a technical stream, as compared to arts or humanities, in higher-secondary education. This gender difference is not caused by any possible variation in cognitive ability between boys and girls. The size of the gender gap is quite substantial considering the average participation in technical stream. Further, the gender gap is not affected by household's affluence; rather, educational parity between parents and better access to technical education help reduce the gender gap.

¹⁸ These questions ask whether the woman decides what to cook on a daily basis, purchase of expensive items, decision on the number of children, decision about health seeking behaviour, purchase of land and properties, etc.

¹⁹ Since the majority of households have one eligible woman, therefore an implication of not having personality information for men is that the variation in women's personality used in the regression is coming from across households, despite having household fixed effects in the regression.

In the second part of our paper, we show that women who have studied a technical stream, especially science, have significantly better labour market outcomes in adult life than those who studied humanities. In many cases, women are able to reap larger benefits from studying technical or STEM subjects than men. Thus, STEM choice by women also significantly reduces the intra-household gender gap in adult-life economic outcomes, such as labour force participation and earnings. Exploring channels for these impacts, we find that STEM choice enables women to participate in salaried employment and in occupations which are usually male-dominated. This result highlights the connection between educational segregation in terms of stream choice at the school level and occupational segregation in the labour market.

In all the analyses presented in this paper, we control for cognitive ability of individuals to mitigate any omitted ability bias in our estimates. We attempt to address the issue of non-cognitive skills by including variables capturing women's personality traits, as reflected by their decision making power within the household and extent of participation in social and political activities outside the household. The results are robust to inclusion of these variables, suggesting that our main findings are not driven by unobservable confounders.

While we acknowledge the potential role of behavioral characteristics of individuals, factors such as access to technical education or attitude towards women's education and economic participation still remain crucial issues in a developing economy. Our analysis suggests that in the context of India, being a girl translates into choosing the type of education which is less rewarding in the labour market. Educational policies should aim at creating incentive for girls to break this barrier and be free to choose subjects which are traditionally dominated by boys. This will potentially have far reaching benefits in reducing the gender gap in labour market outcomes, with benefits to the women affected as well as to larger society.

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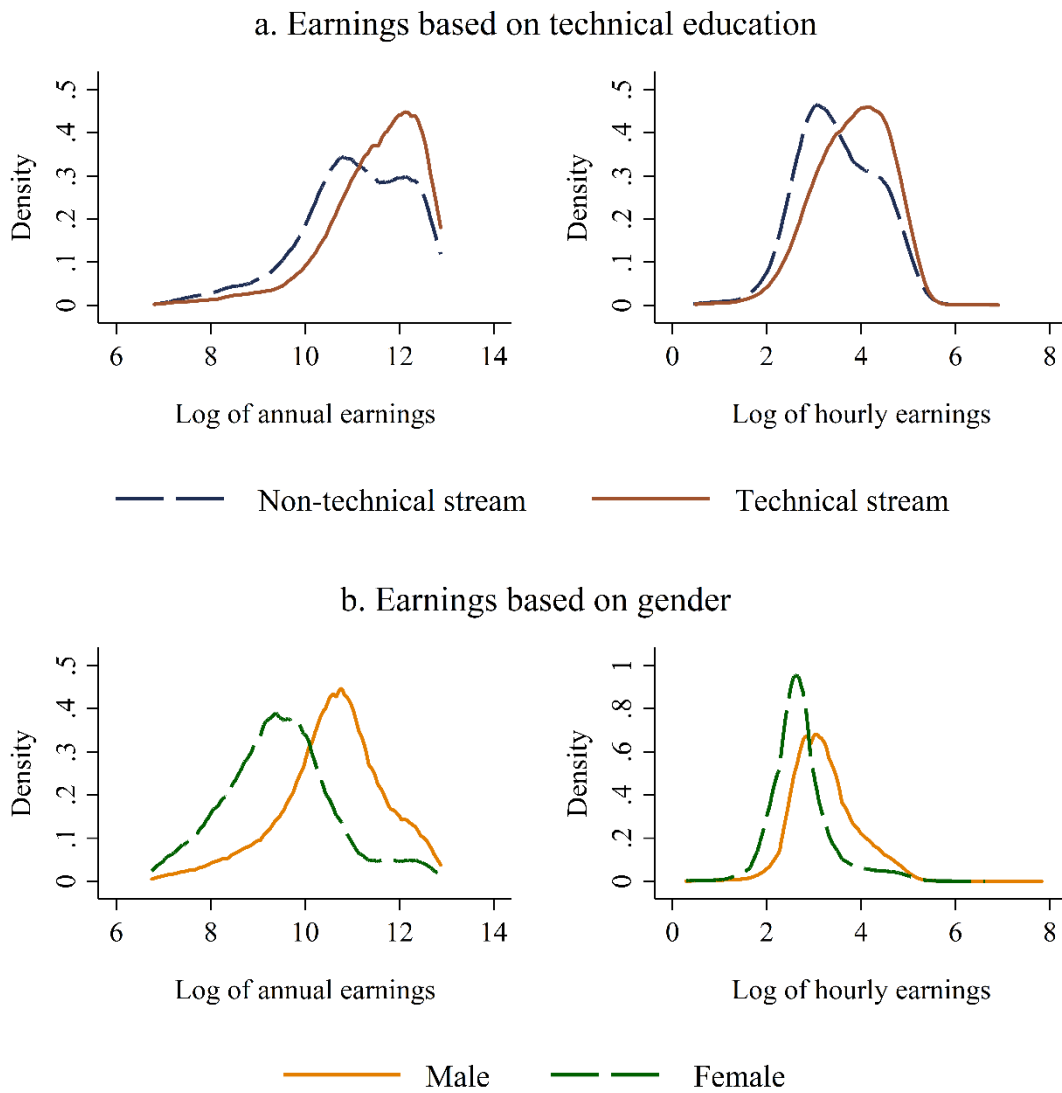
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Figure 1: Kernel density estimates of log of annual and hourly earnings of individuals (aged 25-60 years) based on higher-secondary stream choice and gender



Source: Authors' calculation from IHDS 2011-12 data.

Table 1: Summary statistics

Variable	Obs	Mean	Std. Dev.
<i>Stream choice sample: age 15-18 years</i>			
Female	14845	0.50	0.50
Age (years)	14845	16.49	1.11
Birth order	14845	1.19	0.42
Number of siblings	14845	0.40	0.55
Father's years of education	14845	4.93	4.93
Mother's years of education	14845	3.23	4.34
Secondary pass	14845	0.40	0.49
Technical subject	5213	0.50	0.50
Arts	5213	0.50	0.50
Commerce	5213	0.17	0.37
Science	5213	0.28	0.45
Engineering/Vocational	5213	0.04	0.20
Others	5213	0.01	0.09
Secondary result: 1st division	5928	0.41	0.49
Secondary result: 2nd division	5928	0.47	0.50
Secondary result: 3rd division	5928	0.12	0.33
Math: none	3005	0.04	0.21
Math: number	3005	0.20	0.40
Math: subtraction	3005	0.34	0.47
Math: division	3005	0.42	0.49
Reading: none	3034	0.01	0.11
Reading: letter	3034	0.05	0.22
Reading: word	3034	0.11	0.31
Reading: paragraph	3034	0.24	0.43
Reading: story	3034	0.59	0.49
Writing: none	2992	0.12	0.32
Writing: can write	2992	0.88	0.32
Household income per capita (baseline)	5235	9.68	12.23
Educational parity between parents	5934	-1.67	4.93
Science/technical colleges in district (number per million population)	5707	9.67	10.39
<i>Labour market outcome sample: age 25-60 years</i>			
Labour force participation	80302	0.60	0.49
Salaried employment	80302	0.15	0.35
Casual wage labour	80302	0.29	0.45
Family business	80302	0.08	0.27
Family farm and animal work	80302	0.19	0.40
Male dominated occupation	37348	0.57	0.50
Log of annual earnings	36559	10.16	1.24
Female	80302	0.52	0.50
Age (years)	80302	40.40	10.33
Years of education	80302	5.60	5.23

Secondary pass	80302	0.21	0.41
Secondary pass * Arts	80302	0.14	0.34
Secondary pass * Commerce	80302	0.03	0.17
Secondary pass * Science	80302	0.04	0.19
Secondary pass * Engineering/Vocational	80302	0.01	0.08
Secondary pass * Others	80302	0.002	0.05
Secondary result: 1st division	80302	0.06	0.23
Secondary result: 2nd division	80302	0.12	0.33
Secondary result: 3rd division	80302	0.03	0.17
Marital status: Single	80302	0.07	0.25
Marital status: Married	80302	0.83	0.37
Marital status: Other	80302	0.10	0.30
Relation: Household head	80302	0.36	0.48
Relation: Spouse of head	80302	0.34	0.47
Relation: Son/daughter	80302	0.16	0.37
Relation: Child-in-law	80302	0.08	0.28
Relation: Grandchild	80302	0.003	0.05
Relation: Other	80302	0.05	0.22

Notes: The first set of summary statistics are for the sample of individuals from the stream choice analysis (15-18 years age). The second set corresponds to the labour market outcome regression which focuses on individuals in 25-60 years age-group.

Table 2: Effect of gender on higher-secondary stream choice (probability of choosing technical subjects (Science / Engineering / Vocational / Commerce) versus humanities (Arts))

	Chose technical subjects in higher-secondary education			
	(1)	(2)	(3)	(4)
Female	-0.178*** (0.013)	-0.213*** (0.031)	-0.202** (0.063)	-0.221*** (0.062)
Age (years)	-0.024** (0.008)	0.028 (0.029)	-0.069 (0.070)	-0.058 (0.070)
Birth order	-0.036 (0.025)	0.035 (0.054)	-0.061 (0.122)	-0.065 (0.122)
Number of siblings	-0.007 (0.015)	0.085 (0.115)	0.184 (0.258)	0.236 (0.248)
Father's years of education	0.004* (0.002)	-0.001 (0.009)	-0.031 (0.050)	-0.030 (0.053)
Mother's years of education	0.022*** (0.002)	0.013 (0.017)	-0.004 (0.043)	0.007 (0.045)
Secondary result: 1st division		0.240*** (0.065)		0.200 (0.153)
Secondary result: 2nd division		0.127* (0.057)		0.072 (0.128)
Math: number			-0.016 (0.225)	0.011 (0.188)
Math: subtraction			0.221 (0.227)	0.276 (0.205)
Math: division			0.501* (0.250)	0.563* (0.222)
Reading: word				0.265 (0.312)
Reading: paragraph				0.056 (0.320)
Reading: story				0.116 (0.327)
Writing: can write				-0.108 (0.134)
Constant	0.897*** (0.153)	-0.157 (0.561)	1.709 (1.288)	1.262 (1.278)
Observations	5,213	5,207	2,656	2,634
R-squared	0.086	0.129	0.236	0.283
Household fixed effects	No	Yes	Yes	Yes
Number of households (fixed effects)		4,653	2,515	2,496

The results are from a linear probability model taking children in the age-group of 15-18 years. Robust standard errors clustered at the household level are given in parentheses. *** p<0.001, ** p<0.01, * p<0.05, † p<0.1.

Table 3: Heterogeneity in the effect of gender on higher-secondary stream choice

	Chose technical subjects in higher-secondary education					
	(1)	(2)	(3)	(4)	(5)	(6)
Female	-0.168*** (0.018)	-0.196** (0.074)	-0.166*** (0.014)	-0.181** (0.066)	-0.251*** (0.018)	-0.345*** (0.085)
Female × Household income per capita (baseline)	-0.001 (0.001)	-0.002 (0.004)				
Household income per capita (baseline)	0.003*** (0.001)					
Female × Educational parity between parents			0.007** (0.003)	0.018* (0.009)		
Educational parity between parents			0.018*** (0.002)	0.023 (0.047)		
Female × Science/technical colleges in district (number per million population)					0.008*** (0.001)	0.013* (0.005)
Science/technical colleges in district (number per million population)					0.003** (0.001)	-0.006 (0.016)
Constant	0.827*** (0.162)	1.331 (1.274)	0.896*** (0.152)	1.378 (1.257)	0.707*** (0.157)	-0.379 (1.311)
Observations	4,622	2,634	5,213	2,634	4,998	2,583
R-squared	0.088	0.284	0.087	0.298	0.112	0.321
Other individual covariates	Yes	Yes	Yes	Yes	Yes	Yes
Secondary exam result	No	Yes	No	Yes	No	Yes
Past math score	No	Yes	No	Yes	No	Yes
Past reading & writing score	No	Yes	No	Yes	No	Yes
Household fixed effects	No	Yes	No	Yes	No	Yes
Number of households (fixed effects)		2,496		2,496		2,447

The results are from a linear probability model taking children in the age-group of 15-18 years. Robust standard errors clustered at the household level are given in parentheses. *** p<0.001, ** p<0.01, * p<0.05, † p<0.1.

Table 4: Effect of higher-secondary technical stream choice on adult life labour force participation

	Probability of labour force participation		
	(1) Overall	(2) Rural	(3) Urban
Female	-0.586*** (0.009)	-0.566*** (0.012)	-0.643*** (0.014)
Female \times Secondary pass \times Technical stream (λ)	0.090*** (0.016)	0.107*** (0.030)	0.088*** (0.019)
Secondary pass \times Technical stream (π)	0.005 (0.009)	-0.013 (0.014)	0.001 (0.011)
Female \times Secondary pass	-0.040*** (0.009)	-0.065*** (0.014)	0.027* (0.013)
Secondary result: 1st division	0.024 † (0.012)	-0.012 (0.019)	0.045** (0.017)
Secondary result: 2nd division	0.005 (0.010)	-0.014 (0.014)	0.020 (0.014)
Constant	1.052*** (0.018)	1.082*** (0.023)	0.999*** (0.030)
Effect of Technical stream on females ($\lambda + \pi$)	0.095*** (0.015)	0.094** (0.029)	0.087*** (0.018)
Observations	80,302	51,976	28,326
R-squared	0.665	0.646	0.704
Years of education dummies	Yes	Yes	Yes
Other individual covariates	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes
Number of households (fixed effects)	38,656	25,205	13,451

The results are from a linear probability model taking individuals in the age-group of 25-60 years. Robust standard errors clustered at the household level are given in parentheses. *** p<0.001, ** p<0.01, * p<0.05, † p<0.1.

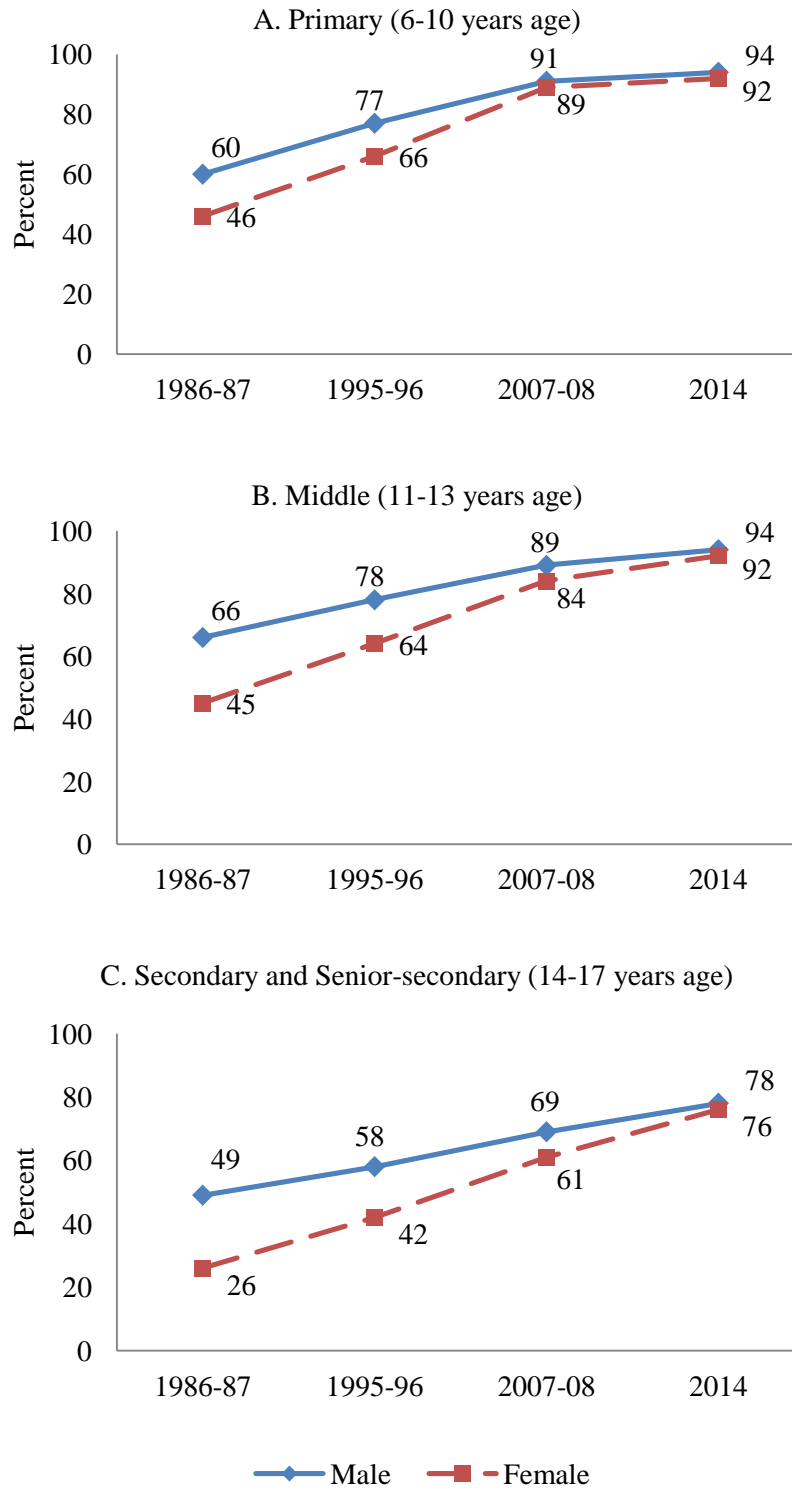
Table 5: Effect of higher-secondary technical stream choice on adult life earnings

	Log of annual earnings					
	Without selection correction			With selection correction		
	(1)	(2)	(3)	(4)	(5)	(6)
	Overall	Rural	Urban	Overall	Rural	Urban
Female	-0.774*** (0.033)	-0.785*** (0.041)	-0.793*** (0.056)	-1.100*** (0.120)	-0.983*** (0.124)	-1.485*** (0.276)
Female \times Secondary pass \times Technical stream (λ)	0.073 (0.082)	-0.177 (0.176)	0.154 † (0.088)	0.118 (0.085)	-0.137 (0.190)	0.282** (0.098)
Secondary pass \times Technical stream (π)	0.007 (0.048)	0.045 (0.081)	0.049 (0.056)	-0.004 (0.047)	0.011 (0.082)	0.014 (0.062)
Female \times Secondary pass	0.367*** (0.057)	0.440*** (0.098)	0.406*** (0.070)	0.348*** (0.057)	0.441*** (0.107)	0.470*** (0.079)
Secondary result: 1st division	0.139* (0.066)	0.096 (0.106)	0.251** (0.078)	0.251*** (0.076)	0.150 (0.115)	0.452*** (0.109)
Secondary result: 2nd division	0.113* (0.056)	0.075 (0.083)	0.179** (0.067)	0.155** (0.056)	0.092 (0.086)	0.266*** (0.076)
Inverse Mills ratio				-1.945** (0.673)	-1.305 † (0.767)	-3.328* (1.295)
Constant	10.413*** (0.075)	10.240*** (0.093)	10.869*** (0.136)	11.715*** (0.453)	11.143*** (0.533)	12.862*** (0.791)
Effect of Technical stream on females ($\lambda + \pi$)	0.080 (0.078)	-0.132 (0.171)	0.203* (0.079)	0.114 (0.081)	-0.126 (0.173)	0.297*** (0.086)
Observations	36,760	25,382	11,378	36,677	25,350	11,327
R-squared	0.371	0.387	0.352	0.371	0.387	0.355
Years of education dummies	Yes	Yes	Yes	Yes	Yes	Yes
Other individual covariates	Yes	Yes	Yes	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of households (fixed effects)	25,511	17,078	8,433	25,452	17,055	8,397

This regression considers salaried/casual wage employees in the age-group of 25-60 years. Robust standard errors clustered at the household level are given in parentheses. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.1$.

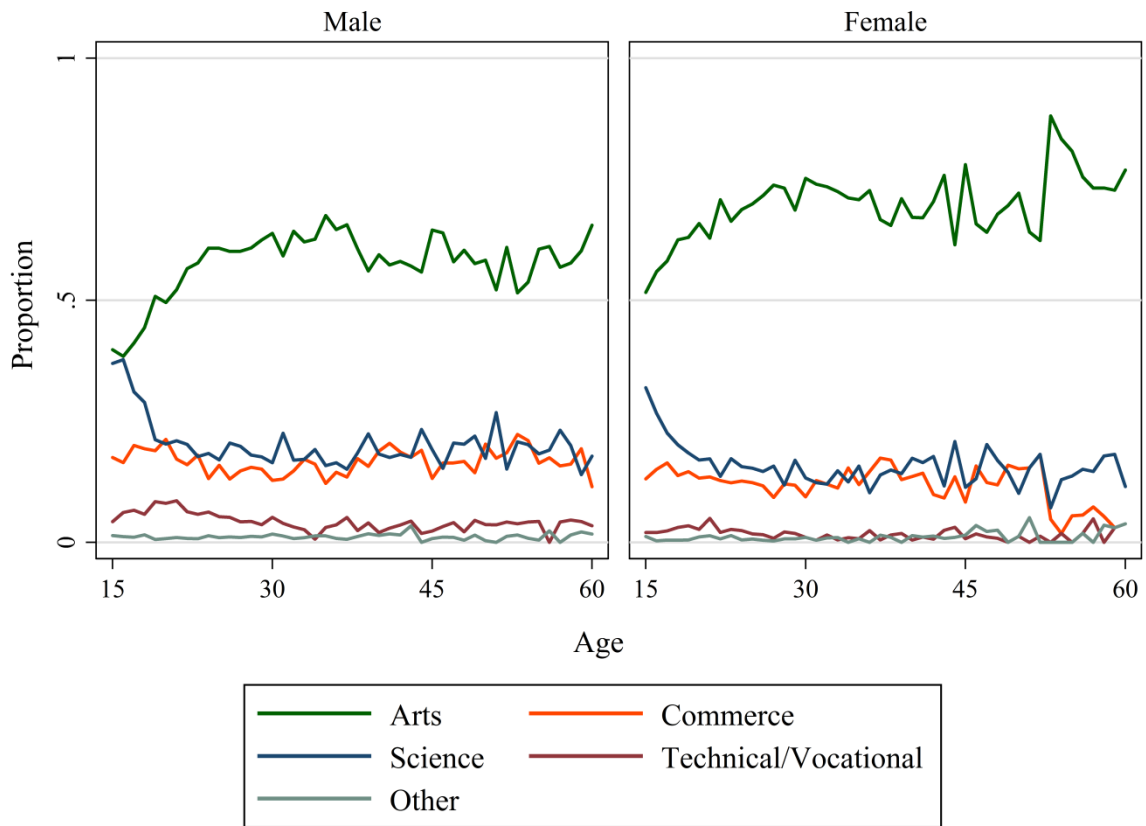
Appendix

Appendix Figure A1: Trends in enrollment rates in India: Estimates from National Sample Surveys



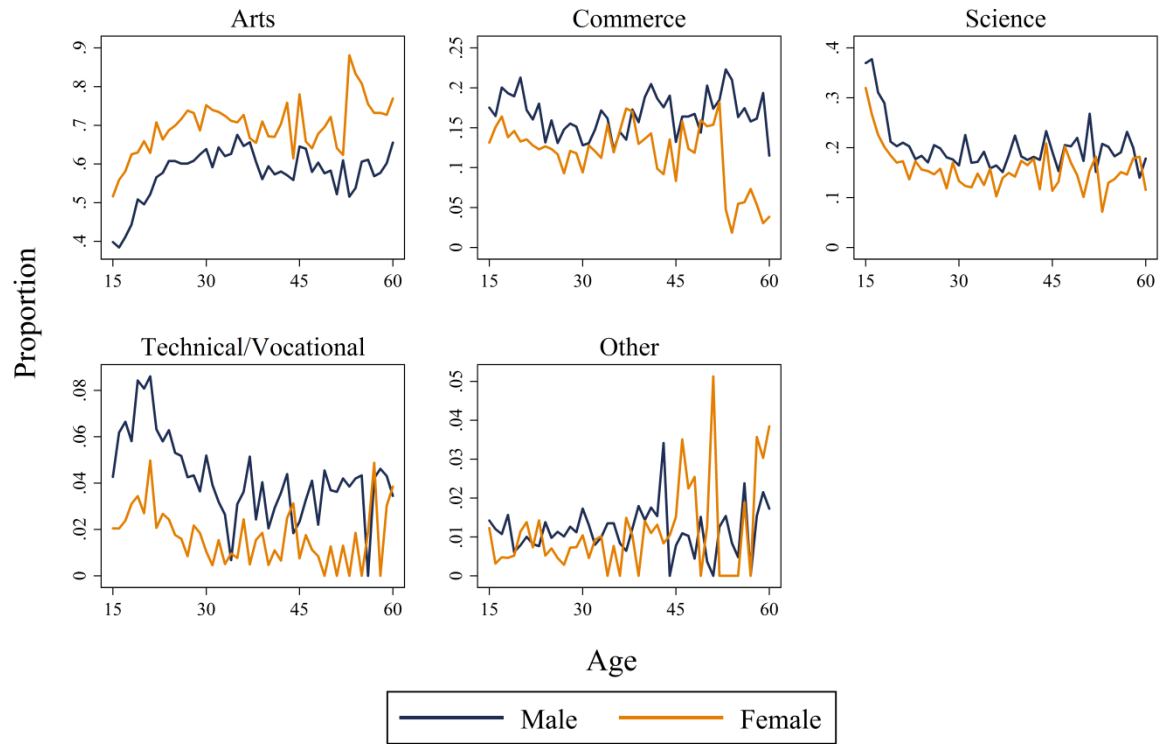
Source: Authors' calculation from multiple rounds of National Sample Survey data.

Appendix Figure A2: Proportion of males and females (aged 15-60 years) in different study streams at the higher-secondary level



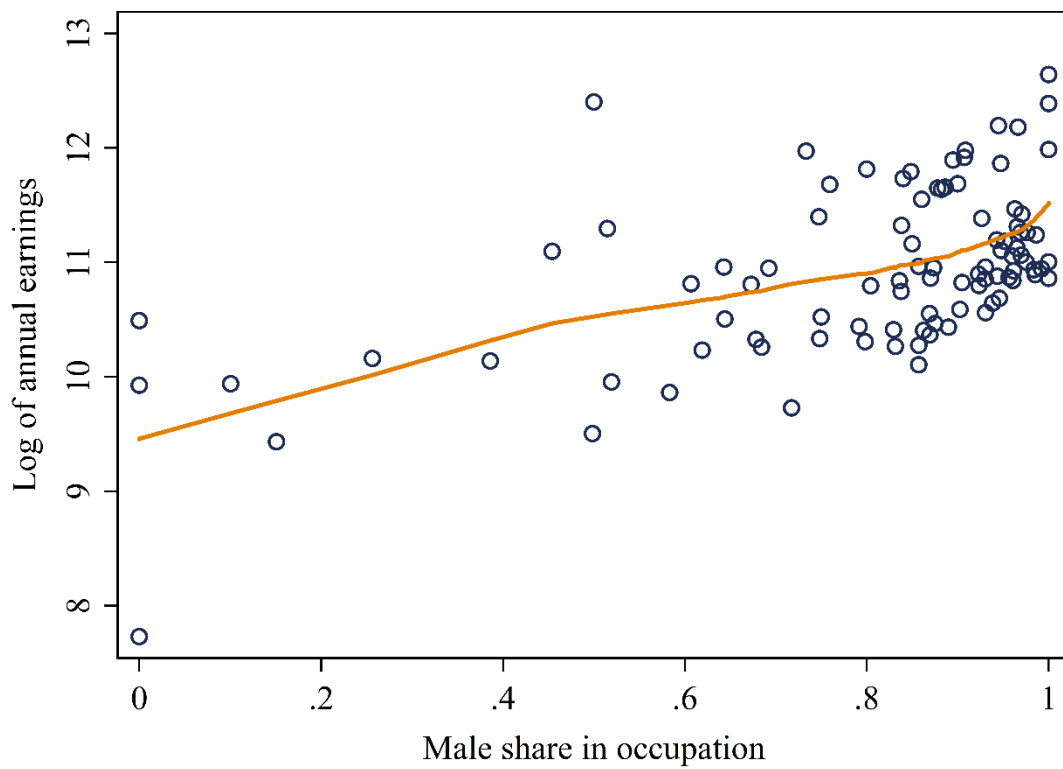
Source: Authors' calculation from IHDS 2011-12 data.

Appendix Figure A3: Raw gender differences in the choice of study streams at the higher-secondary level for individuals aged 15-60 years



Source: Authors' calculation from IHDS 2011-12 data.

Appendix Figure A4: Relationship between male share in occupation and average earnings in occupation (scatter plot and lowess smoother)



Source: Authors' calculations from IHDS 2011-12 data.

Appendix Table A1: Effect of gender on the probability of secondary level completion

	Completed secondary level of education			
	(1)	(2)	(3)	(4)
Female	0.012† (0.007)	-0.013 (0.013)	0.018 (0.026)	0.023 (0.026)
Age (years)	0.134*** (0.004)	0.089*** (0.011)	0.089*** (0.026)	0.086** (0.027)
Birth order	-0.024† (0.012)	-0.103*** (0.023)	-0.094† (0.052)	-0.085 (0.053)
Number of siblings	-0.003 (0.010)	0.074* (0.038)	0.242 (0.151)	0.272† (0.148)
Father's years of education	0.015*** (0.001)	0.007 (0.005)	-0.022† (0.012)	-0.020† (0.012)
Mother's years of education	0.027*** (0.001)	0.001 (0.011)	-0.017 (0.014)	-0.016 (0.014)
Math: number			0.021 (0.044)	0.017 (0.047)
Math: subtraction			0.106* (0.050)	0.069 (0.058)
Math: division			0.338*** (0.058)	0.285*** (0.066)
Reading: letter				0.007 (0.057)
Reading: word				-0.038 (0.057)
Reading: paragraph				0.005 (0.068)
Reading: story				0.064 (0.077)
Writing: can write				0.027 (0.041)
Constant	-1.953*** (0.069)	-1.012*** (0.212)	-0.976* (0.496)	-0.982† (0.502)
Observations	14,845	14,845	7,408	7,348
R-squared	0.208	0.207	0.326	0.330
Household fixed effects	No	Yes	Yes	Yes
Number of households (fixed effects)		11,636	6,560	6,512

The results are from a linear probability model taking children in the age-group of 15-18 years. Robust standard errors clustered at the household level are given in parentheses. *** p<0.001, ** p<0.01, * p<0.05, † p<0.1.

Appendix Table A2: Marginal effects from multinomial logit model for the effect of gender on probability of choosing different study streams at the higher-secondary level of education

	Probability of choosing at higher-secondary level:				
	Arts (1)	Commerce (2)	Science (3)	Engineering / Vocational (4)	Others (5)
Female	0.220*** (0.039)	-0.088** (0.033)	-0.095* (0.039)	-0.025 (0.018)	-0.012 (0.013)
Age (years)	-0.038 (0.040)	0.004 (0.033)	0.024 (0.036)	0.007 (0.016)	0.003 (0.006)
Secondary result: 1st division	-0.281*** (0.069)	0.053 (0.062)	0.231*** (0.067)	-0.000 (0.025)	-0.002 (0.012)
Secondary result: 2nd division	-0.050 (0.061)	0.024 (0.054)	0.020 (0.065)	-0.004 (0.026)	0.010 (0.014)
Math: number	-0.158 (0.134)	-0.266* (0.117)	-0.144 (0.131)	0.558*** (0.097)	0.009 (0.023)
Math: subtraction	-0.359* (0.148)	-0.203 (0.124)	-0.107 (0.140)	0.649*** (0.110)	0.019 (0.022)
Math: division	-0.396* (0.156)	-0.142 (0.138)	-0.087 (0.145)	0.597*** (0.105)	0.028 (0.029)
Reading: word	-0.085 (0.140)	0.119 (0.105)	-0.039 (0.153)	0.030 (0.053)	-0.026 (0.037)
Reading: paragraph	-0.093 (0.151)	0.125 (0.104)	-0.040 (0.160)	0.015 (0.061)	-0.008 (0.024)
Reading: story	-0.133 (0.155)	0.155 (0.114)	-0.008 (0.164)	0.008 (0.067)	-0.022 (0.023)
Writing: can write	0.288** (0.101)	-0.150* (0.075)	-0.094 (0.095)	-0.022 (0.045)	-0.021 (0.019)
Observations	2,634	2,634	2,634	2,634	2,634
Additional controls	Yes	Yes	Yes	Yes	Yes
Household fixed effects (Mundlak)	Yes	Yes	Yes	Yes	Yes

The results are marginal effects estimated from a multinomial logit model taking children in the age-group of 15-18 years. Control variables included are according to column 4 of Table 3. Robust standard errors clustered at the household level are given in parentheses. *** p<0.001, ** p<0.01, * p<0.05, † p<0.1.

Appendix Table A3: Effect of higher-secondary subject choice on adult life labour force participation

	Probability of labour force participation		
	(1) Overall	(2) Rural	(3) Urban
Female	-0.587*** (0.009)	-0.566*** (0.012)	-0.645*** (0.014)
Female × Secondary pass × Commerce	-0.009 (0.021)	0.046 (0.042)	-0.019 (0.024)
Female × Secondary pass × Science	0.160*** (0.022)	0.123** (0.041)	0.178*** (0.026)
Female × Secondary pass × Engineering/Vocational	0.217** (0.072)	0.359** (0.114)	0.137 (0.091)
Female × Secondary pass × Others	0.003 (0.075)	-0.095 (0.119)	0.086 (0.098)
Secondary pass × Commerce	0.021† (0.012)	-0.037† (0.022)	0.026† (0.014)
Secondary pass × Science	0.001 (0.011)	0.015 (0.018)	-0.014 (0.015)
Secondary pass × Engineering/Vocational	-0.027 (0.026)	-0.084* (0.041)	-0.006 (0.033)
Secondary pass × Others	-0.037 (0.041)	0.041 (0.048)	-0.118† (0.065)
Female × Secondary pass	-0.040*** (0.009)	-0.065*** (0.014)	0.027* (0.013)
Secondary result: 1st division	0.023† (0.013)	-0.014 (0.019)	0.044** (0.017)
Secondary result: 2nd division	0.004 (0.010)	-0.016 (0.014)	0.021 (0.014)
Constant	1.053*** (0.018)	1.082*** (0.023)	1.001*** (0.030)
Observations	80,302	51,976	28,326
R-squared	0.666	0.647	0.705
Years of education dummies	Yes	Yes	Yes
Other individual covariates	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes
Number of households (fixed effects)	38,656	25,205	13,451

The results are from linear probability model taking individuals in the age-group of 25-60 years. Robust standard errors clustered at the household level are given in parentheses. *** p<0.001, ** p<0.01, * p<0.05, † p<0.1.

Appendix Table A4: Effect of higher-secondary technical stream choice on salaried employment versus other employment in adult life

	Probability of salaried employment as compared to other employment		
	(1) Overall	(2) Rural	(3) Urban
Female	-0.006 (0.010)	-0.023* (0.011)	0.063** (0.024)
Female \times Secondary pass \times Technical stream (λ)	0.115*** (0.030)	0.094† (0.050)	0.098* (0.040)
Secondary pass \times Technical stream (π)	-0.013 (0.016)	0.020 (0.022)	-0.031 (0.024)
Female \times Secondary pass	0.029 (0.018)	0.018 (0.023)	-0.002 (0.030)
Secondary result: 1st division	0.098*** (0.023)	0.077** (0.030)	0.130*** (0.037)
Secondary result: 2nd division	0.056** (0.018)	0.048* (0.021)	0.072* (0.032)
Constant	0.159*** (0.024)	0.076** (0.026)	0.304*** (0.058)
Effect of Technical stream on females ($\lambda + \pi$)	0.102*** (0.029)	0.115* (0.048)	0.067† (0.037)
Observations	57,735	41,170	16,565
R-squared	0.095	0.113	0.08
Years of education dummies	Yes	Yes	Yes
Other individual covariates	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes
Number of households (fixed effects)	34,622	23,367	11,255

The results are from a linear probability model taking employed individuals in the age-group of 25-60 years. Robust standard errors clustered at the household level are given in parentheses. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.1$.

Appendix Table A5: Effect of higher-secondary technical stream choice on different types of employment

	Probability of choosing:								
	Casual wage			Family business			Family farm and animal work		
	(1) Overall	(2) Rural	(3) Urban	(4) Overall	(5) Rural	(6) Urban	(7) Overall	(8) Rural	(9) Urban
Female	-0.173*** (0.012)	-0.167*** (0.014)	-0.190*** (0.022)	-0.015† (0.008)	-0.012 (0.008)	-0.032† (0.019)	0.194*** (0.011)	0.202*** (0.014)	0.159*** (0.015)
Female × Secondary pass × Technical stream (λ)	-0.002 (0.019)	-0.019 (0.037)	-0.016 (0.021)	0.018 (0.024)	0.047 (0.035)	-0.004 (0.035)	-0.131*** (0.021)	-0.123* (0.050)	-0.078*** (0.017)
Secondary pass × Technical stream (π)	-0.031** (0.011)	-0.026 (0.017)	-0.027* (0.014)	-0.009 (0.013)	-0.027 (0.017)	0.024 (0.021)	0.053*** (0.013)	0.033 (0.022)	0.034** (0.012)
Female × Secondary pass	0.096*** (0.012)	0.060*** (0.018)	0.134*** (0.020)	-0.070*** (0.014)	-0.073*** (0.016)	-0.028 (0.025)	-0.054*** (0.015)	-0.005 (0.024)	-0.104*** (0.017)
Secondary result: 1st division	-0.028 (0.017)	-0.037 (0.025)	-0.021 (0.022)	-0.046* (0.018)	0.000 (0.021)	-0.091** (0.032)	-0.025 (0.018)	-0.040 (0.030)	-0.018 (0.015)
Secondary result: 2nd division	-0.030* (0.015)	-0.032 (0.020)	-0.033 (0.020)	0.004 (0.014)	0.019 (0.015)	-0.022 (0.028)	-0.029† (0.015)	-0.034 (0.022)	-0.017 (0.014)
Constant	0.635*** (0.029)	0.723*** (0.034)	0.414*** (0.055)	0.105*** (0.019)	0.070*** (0.020)	0.250*** (0.047)	0.101*** (0.027)	0.130*** (0.034)	0.032 (0.036)
Effect of Technical stream on females ($\lambda + \pi$)	-0.033† (0.018)	-0.045 (0.035)	-0.043* (0.020)	0.009 (0.023)	0.020 (0.032)	0.020 (0.032)	-0.078*** (0.021)	-0.089† (0.049)	-0.044* (0.017)
Observations	57,735	41,170	16,565	57,735	41,170	16,565	57,735	41,170	16,565
R-squared	0.085	0.092	0.069	0.022	0.024	0.036	0.211	0.219	0.194
Years of education dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other individual covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of households (fixed effects)	34,622	23,367	11,255	34,622	23,367	11,255	34,622	23,367	11,255

The results are from linear probability model taking employed individuals in the age-group of 25-60 years. Robust standard errors clustered at the household level are given in parentheses. *** p<0.001, ** p<0.01, * p<0.05, † p<0.1.

Appendix Table A6: Effect of higher-secondary subject choice on salaried employment versus other employment in adult life

	Probability of salaried employment as compared to other employment		
	(1) Overall	(2) Rural	(3) Urban
Female	-0.007 (0.010)	-0.024* (0.011)	0.062** (0.024)
Female × Secondary pass × Commerce	0.073 (0.047)	0.008 (0.079)	0.074 (0.059)
Female × Secondary pass × Science	0.157*** (0.035)	0.195** (0.060)	0.123** (0.046)
Female × Secondary pass × Engineering/Vocational	-0.020 (0.091)	-0.054 (0.130)	0.012 (0.130)
Female × Secondary pass × Others	0.235 (0.153)	0.430† (0.227)	0.127 (0.207)
Secondary pass × Commerce	-0.028 (0.021)	-0.004 (0.032)	-0.035 (0.030)
Secondary pass × Science	-0.002 (0.020)	0.036 (0.030)	-0.030 (0.029)
Secondary pass × Engineering/Vocational	0.029 (0.042)	0.096 (0.060)	-0.025 (0.058)
Secondary pass × Others	-0.078 (0.067)	-0.036 (0.076)	-0.126 (0.127)
Female × Secondary pass	0.027 (0.018)	0.016 (0.023)	-0.004 (0.030)
Secondary result: 1st division	0.095*** (0.023)	0.072* (0.030)	0.129*** (0.037)
Secondary result: 2nd division	0.055** (0.018)	0.046* (0.021)	0.071* (0.032)
Constant	0.158*** (0.024)	0.076** (0.026)	0.302*** (0.058)
Observations	57,735	41,170	16,565
R-squared	0.096	0.115	0.081
Years of education dummies	Yes	Yes	Yes
Other individual covariates	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes
Number of households (fixed effects)	34,622	23,367	11,255

The results are from a linear probability model taking employed individuals in the age-group of 25-60 years. Robust standard errors clustered at the household level are given in parentheses. *** p<0.001, ** p<0.01, * p<0.05, † p<0.1.

Appendix Table A7: Effect of higher-secondary technical stream choice on participation in male-dominated occupations in adult life

	Probability of participating in male-dominated occupations as compared to other occupations		
	(1) Overall	(2) Rural	(3) Urban
Female	-0.213*** (0.017)	-0.164*** (0.019)	-0.383*** (0.034)
Female \times Secondary pass \times Technical stream (λ)	0.049 (0.043)	-0.021 (0.077)	0.123* (0.052)
Secondary pass \times Technical stream (π)	0.022 (0.023)	0.048 (0.039)	-0.017 (0.029)
Female \times Secondary pass	-0.165*** (0.026)	-0.124** (0.040)	-0.057 (0.038)
Secondary result: 1st division	-0.022 (0.033)	-0.053 (0.053)	0.000 (0.043)
Secondary result: 2nd division	-0.014 (0.027)	-0.049 (0.038)	0.022 (0.036)
Constant	0.730*** (0.039)	0.702*** (0.050)	0.835*** (0.066)
Effect of Technical stream on females ($\lambda + \pi$)	0.071† (0.042)	0.027 (0.075)	0.105* (0.051)
Observations	37,552	25,742	11,810
R-squared	0.160	0.122	0.304
Years of education dummies	Yes	Yes	Yes
Other individual covariates	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes
Number of households (fixed effects)	25,954	17,252	8,702

The results are from linear probability model taking employed individuals in the age-group of 25-60 years. Robust standard errors clustered at the household level are given in parentheses. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.1$.

Appendix Table A8: Effect of higher-secondary subject choice on participation in male-dominated occupations in adult life

	Probability of participating in male-dominated occupations as compared to other occupations		
	(1) Overall	(2) Rural	(3) Urban
Female	-0.214*** (0.017)	-0.163*** (0.019)	-0.386*** (0.034)
Female × Secondary pass × Commerce	0.190** (0.062)	0.085 (0.141)	0.271*** (0.070)
Female × Secondary pass × Science	0.029 (0.053)	-0.076 (0.088)	0.121† (0.065)
Female × Secondary pass × Engineering/Vocational	-0.093 (0.138)	0.020 (0.220)	-0.178 (0.159)
Female × Secondary pass × Others	-0.109 (0.194)	-0.117 (0.260)	-0.092 (0.242)
Secondary pass × Commerce	0.053† (0.029)	0.087 (0.054)	0.016 (0.034)
Secondary pass × Science	-0.040 (0.031)	-0.004 (0.053)	-0.089* (0.038)
Secondary pass × Engineering/Vocational	0.182*** (0.051)	0.154 (0.095)	0.190*** (0.056)
Secondary pass × Others	-0.089 (0.094)	-0.061 (0.091)	-0.146 (0.171)
Female × Secondary pass	-0.170*** (0.026)	-0.123** (0.040)	-0.067† (0.038)
Secondary result: 1st division	-0.018 (0.033)	-0.047 (0.053)	0.002 (0.043)
Secondary result: 2nd division	-0.010 (0.027)	-0.045 (0.039)	0.023 (0.036)
Constant	0.729*** (0.039)	0.704*** (0.050)	0.835*** (0.065)
Observations	37,552	25,742	11,810
R-squared	0.163	0.123	0.311
Years of education dummies	Yes	Yes	Yes
Other individual covariates	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes
Number of households (fixed effects)	25,954	17,252	8,702

The results are from a linear probability model taking employed individuals in the age-group of 25-60 years. Robust standard errors clustered at the household level are given in parentheses. *** p<0.001, ** p<0.01, * p<0.05, † p<0.1.

Appendix Table A9: Effect of higher-secondary subject choice on adult life earnings

	Log of annual earnings					
	Without selection correction			With selection correction		
	(1)	(2)	(3)	(4)	(5)	(6)
	Overall	Rural	Urban	Overall	Rural	Urban
Female	-0.774*** (0.033)	-0.787*** (0.041)	-0.792*** (0.056)	-1.104*** (0.121)	-0.998*** (0.125)	-1.489*** (0.280)
Female × Secondary pass × Commerce	0.040 (0.121)	-0.289 (0.277)	0.152 (0.128)	0.016 (0.119)	-0.255 (0.291)	0.143 (0.124)
Female × Secondary pass × Science	0.165† (0.094)	0.014 (0.183)	0.203† (0.104)	0.273** (0.101)	0.112 (0.202)	0.416** (0.133)
Female × Secondary pass × Engineering/Vocational	-0.520 (0.362)	-0.711 (0.728)	-0.455 (0.278)	-0.449 (0.398)	-0.619 (0.862)	-0.345 (0.302)
Female × Secondary pass × Others	0.200 (0.587)	-0.188 (0.897)	0.363 (0.575)	0.286 (0.689)	-0.089 (0.938)	0.503 (0.714)
Secondary pass × Commerce	-0.051 (0.056)	0.006 (0.096)	-0.020 (0.067)	-0.041 (0.055)	-0.052 (0.102)	-0.002 (0.072)
Secondary pass × Science	0.010 (0.064)	0.033 (0.114)	0.055 (0.072)	-0.023 (0.066)	-0.008 (0.116)	-0.007 (0.079)
Secondary pass × Engineering/Vocational	0.149 (0.101)	0.046 (0.192)	0.313** (0.104)	0.167† (0.101)	0.056 (0.216)	0.311** (0.111)
Secondary pass × Others	0.089 (0.202)	0.387 (0.335)	-0.197 (0.182)	0.026 (0.200)	0.353 (0.363)	-0.369† (0.208)
Female × Secondary pass	0.367*** (0.057)	0.440*** (0.098)	0.404*** (0.071)	0.346*** (0.057)	0.437*** (0.107)	0.473*** (0.080)
Secondary result: 1st division	0.134* (0.066)	0.091 (0.107)	0.239** (0.077)	0.249** (0.076)	0.148 (0.117)	0.444*** (0.109)
Secondary result: 2nd division	0.115* (0.056)	0.080 (0.083)	0.176** (0.066)	0.159** (0.056)	0.099 (0.086)	0.267*** (0.076)
Inverse Mills ratio				-1.974** (0.677)	-1.382† (0.769)	-3.351* (1.308)
Constant	10.407*** (0.075)	10.236*** (0.093)	10.861*** (0.136)	11.729*** (0.456)	11.192*** (0.535)	12.869*** (0.797)
Observations	36,760	25,382	11,378	36,677	25,350	11,327
R-squared	0.371	0.388	0.354	0.372	0.388	0.357
Years of education dummies	Yes	Yes	Yes	Yes	Yes	Yes
Other individual covariates	Yes	Yes	Yes	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of households (fixed effects)	25,511	17,078	8,433	25,452	17,055	8,397

This regression considers salaried/casual wage employees in the age-group of 25-60 years. Robust standard errors clustered at the household level are given in parentheses. *** p<0.001, ** p<0.01, * p<0.05, † p<0.1.

Appendix Table A10: Effect of higher-secondary technical stream choice on adult life working-intensity and hourly earnings

	Work intensity (annual hours of work)			Log of hourly earnings		
	(1)	(2)	(3)	(4)	(5)	(6)
	Overall	Rural	Urban	Overall	Rural	Urban
Female	-599.163*** (101.146)	-550.627*** (104.402)	-668.059** (235.398)	-0.488*** (0.077)	-0.401*** (0.064)	-0.843*** (0.176)
Female × Secondary pass × Technical stream (λ)	120.184† (67.800)	29.647 (127.272)	211.411* (91.669)	0.029 (0.068)	-0.162 (0.116)	0.146† (0.088)
Secondary pass × Technical stream (π)	4.990 (40.808)	-6.694 (68.793)	6.736 (50.586)	0.003 (0.034)	0.018 (0.052)	0.011 (0.046)
Female × Secondary pass	204.730*** (47.483)	311.972*** (76.765)	220.495** (73.511)	0.076† (0.043)	0.111† (0.066)	0.207** (0.064)
Secondary result: 1st division	78.895 (65.916)	194.424* (94.095)	6.428 (107.912)	0.167** (0.051)	0.016 (0.069)	0.382*** (0.082)
Secondary result: 2nd division	110.160* (49.164)	109.870 (67.085)	99.023 (79.974)	0.056 (0.037)	-0.000 (0.046)	0.164** (0.056)
Inverse Mills ratio	-1,145.381* (581.566)	-772.252 (639.485)	-1,356.518 (1,122.939)	-0.767† (0.438)	-0.351 (0.397)	-1.964* (0.817)
Constant	2,710.602*** (390.144)	2,306.489*** (438.314)	3,186.124*** (682.647)	3.515*** (0.294)	3.185*** (0.274)	4.331*** (0.500)
Effect of Technical stream on females ($\lambda + \pi$)	125.174* (62.816)	22.953 (116.542)	218.147** (77.435)	0.032 (0.062)	-0.144 (0.116)	0.157* (0.075)
Observations	36,646	25,325	11,321	36,646	25,325	11,321
R-squared	0.232	0.249	0.209	0.238	0.276	0.222
Years of education dummies	Yes	Yes	Yes	Yes	Yes	Yes
Other individual covariates	Yes	Yes	Yes	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of households (fixed effects)	25,432	17,038	8,394	25,432	17,038	8,394

This regression considers salaried/casual wage employees in the age-group of 25-60 years. Bootstrapped standard errors clustered at the household level are given in parentheses. *** p<0.001, ** p<0.01, * p<0.05, † p<0.1.

Appendix Table A11: Robustness of results to inclusion of additional control variables capturing women's personality traits

	Labour force participation			Log of annual earnings		
	(1)	(2)	(3)	(4)	(5)	(6)
	Overall	Rural	Urban	Overall	Rural	Urban
Female	-0.619*** (0.012)	-0.587*** (0.016)	-0.699*** (0.020)	-0.929*** (0.123)	-0.942*** (0.130)	-1.436*** (0.295)
Female × Secondary pass × Technical stream (λ)	0.074*** (0.018)	0.094** (0.036)	0.082*** (0.022)	0.098 (0.094)	-0.032 (0.183)	0.239* (0.117)
Secondary pass × Technical stream (π)	0.008 (0.009)	0.000 (0.015)	-0.003 (0.012)	-0.025 (0.049)	-0.015 (0.089)	-0.021 (0.060)
Female × Secondary pass	-0.063*** (0.010)	-0.074*** (0.015)	-0.007 (0.014)	0.331*** (0.066)	0.414*** (0.111)	0.448*** (0.089)
Secondary result: 1st division	0.027* (0.014)	-0.005 (0.020)	0.049** (0.019)	0.227** (0.081)	0.241* (0.118)	0.399*** (0.115)
Secondary result: 2nd division	0.003 (0.011)	-0.021 (0.015)	0.024 (0.015)	0.151* (0.060)	0.132 (0.088)	0.244** (0.080)
Index of intra-household decision making power	0.013*** (0.001)	0.015*** (0.002)	0.010*** (0.002)	0.011 † (0.007)	0.016* (0.007)	0.002 (0.019)
Index of social and political participation	0.043*** (0.003)	0.051*** (0.003)	0.022*** (0.004)	0.026 † (0.014)	0.040* (0.017)	-0.009 (0.019)
Inverse Mills ratio				-0.921 (0.721)	-1.116 (0.825)	-2.791* (1.352)
Constant	1.064*** (0.024)	1.082*** (0.031)	1.039*** (0.040)	10.955*** (0.471)	10.916*** (0.567)	12.603*** (0.824)
Effect of Technical stream on females ($\lambda + \pi$)	0.082*** (0.018)	0.094** (0.034)	0.079*** (0.021)	0.073 (0.089)	-0.047 (0.173)	0.219* (0.108)
Observations	69,565	45,287	24,278	34,158	23,627	10,531
R-squared	0.685	0.666	0.729	0.371	0.383	0.371
Years of education dummies	Yes	Yes	Yes	Yes	Yes	Yes
Other individual covariates	Yes	Yes	Yes	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of households (fixed effects)	36,769	23,956	12,813	24,525	16,451	8,074

Robust standard errors (bootstrapped for columns 4-6) clustered at the household level are given in parentheses. *** p<0.001, ** p<0.01, * p<0.05, † p<0.1.