ESSAYS ON LABOUR MARKET OUTCOMES OF WOMEN IN PUNJAB

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I certify that I have read this dissertation and that, in my opinion, it is fully adequate in scope and quality to be considered for the degree of Doctor of Philosophy.

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by

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Abstract

Gender inequality is prevalent in almost all social and economic outcomes in Pakistan. In this thesis, we, however, focus only on the labour market outcomes of women and explore the likely determinants of these outcomes to better understand the source of gender inequality in these outcomes. The two labour market outcomes of women in Punjab that this thesis analyses are wages in chapters 2 and 3 and female labour force participation in chapter 4. The three drivers of these labour market outcomes that we primarily focus on in each of the chapters are job opportunities in chapter 2, years of education in chapter 3 and a motivational nudge in chapter 4.

Our findings from the first chapter indicate that the gender wage gap for individuals with tertiary education increased from 2006 to 2014. Using the Oaxaca Blinder methodology, we find that the unexplained gap which contributes almost three-fourths to the gender wage gap has mainly increased over the years. Furthermore, controlling for the excess supply of women in limited jobs decreases the unexplained gap but this effect fades away when we account for selection into higher education. The second chapter using Instrumental Variable methodology shows that the gender wage gap tends to fall with the years of education as the incremental benefit to one extra year of education is higher for women than men. The third chapter documents findings from a randomized controlled trial that tests the effectiveness of a motivational nudge in the form of role model stories on the job search effort and work status of female students who are graduates of Public colleges in Lahore. We find no effect of the nudge on either job search effort or work status.

Thesis supervisor: Naved Hamid
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1. Introduction

According to recent figures by the Bureau of Statistics, women constitute 49 percent of the country's population, and only a quarter of them (22.5%) participate in the labour force (Labour Force Survey, 2018). A comparison of the Labor Force Participation Rate of women with that of men at 70% (Labour Force Survey, 2018) shows how underutilized a huge proportion of the population in Pakistan is. Apart from that, it also points to stark gender inequality. Gender inequality is also reflected in the returns of those participating in the labour force, with the gender pay gap at 34%, a figure twice that of the global average (ILO, 2019). Similarly, occupational choices and educational attainments also differ significantly between men and women in Pakistan. For instance, there are only 39.1% of females in the age range of 15-64 years with some formal education as opposed to 70% of males (Labour Force Survey, 2018).

The situation is not different at the provincial level either. Punjab is Pakistan's largest province in terms of population. Out of a population of 110 million, 51% are men, and 49% are women (Punjab Commission for Status of Women, 2018). The female labour force participation rate in Punjab is 27% compared to 71% for men (Labour Force Survey, 2018). The percentage of males with some formal education who lie within the age range of 15-64 years is 71.8% compared to 55.2% for females (Labour Force Survey, 2018). There are also disparities in the wages earned by men and women. For instance, the sectors where the employment of women is the highest, i.e., Agriculture and Education, 25% and 6%, respectively, of women earn less than Rs 5000 per month compared to only 1.5% and 0.3% of men, respectively (Punjab Commission for Status of Women, 2018). Given this gender disparity, in this thesis, we study the labour market outcomes of women and explore the likely determinants of these outcomes to better understand the source of this inequality.

There is no shortage of literature that shows the significance of gender equality for economic growth and development. Seminal work by Galor (1996) and Lagerlof (2003) shows that gender equality and economic growth are linked. Galor (1996), for instance, shows that a rise in women's wages causes fertility to fall due to an increase in the opportunity cost of not working for women. This decrease in population leads to an increase in capital per worker, thereby increasing the pace of economic growth. Lagerlof (2003) explains Europe's economic growth and development by relating it to gender inequality and how it has evolved. He points to a positive relationship between gender equality in education and economic growth, as increased education of women lowers fertility and increases human capital accumulation.

More recent literature addresses the significance of gender equality by documenting the economic costs associated with it; for instance, there is substantial evidence of the negative impacts of the wage gap on output per capita (Cavalcanti and Tavares, 2016), genderwise occupational segregation on entrepreneurial talent, human capital accumulation, technology adoption and innovation, which are key drivers of growth (Esteve-Volart, 2009). Similarly, Cuberes and Teignier (2016) highlight in their work the negative consequences of restricting access to occupations based on gender. They argue that aggregate productivity and hence income per capita would fall if all women are excluded from managerial positions, as this may lead to a fall in the average talent of managers. Lee (2020) similarly shows that the gender inequality in nonagricultural sectors causes misallocation of talented females to unsuitable agricultural activities reducing average productivity in the agricultural sector.

It is therefore imperative to understand the various factors that may contribute to the gender gap in labour market outcomes. This particular thesis analyses two labour market outcomes of women in Punjab, namely, wages in chapters 2 and 3 and female labour force participation in chapter 4. In each of the chapters, we empirically examine the determinants of these labour market outcomes. The three determinants that we primarily focus on in our thesis for studying various labour market outcomes are job opportunities in chapter 2, years of education in chapter 3 and a motivational nudge in chapter 4. A brief account of each of the individual chapters along with a justification for why we choose to use these determinants is what follows next.

Chapter 2 of this thesis aims to estimate the gender wage gap in Punjab for individuals with tertiary education and understand the likely causes of it. The motivation behind conducting this analysis is the trend in the prime human capital determinants of men and women in Punjab. While women in Punjab seem to be catching up with men in terms of the prime human capital determinants, i.e., education and experience with there being a greater number of women enrolled in graduate classes compared to men and the gender gap in postgraduate classes smaller (and shrinking over time) than that at the secondary and lower levels. Similarly, the gap in the average years of experience also seems to be shrinking. On the other hand, the gender wage gap has consistently increased over the last decade. This chapter aims to find a solution to this puzzle by asking if the prime human capital determinants that are crucial for determining wage are improving for women, then why is the gender wage gap not shrinking subsequently. This chapter uses wage decomposition analysis to understand the likely causes of the widening gender wage gap over time by decomposing the wage gap into an ‘endowment effect’ and a coefficient effect’, also known popularly in the literature as observed and unobserved gaps, respectively.

However, the sample that we have chosen to work with, highly educated individuals who are in paid employment, is a very selected sample. Estimating a wage equation for this selected sample is not without the risk of obtaining biased estimates. Selection bias in our results may originate from two sources. First, individuals who enter into paid employment as opposed to being self-employed or not being in the labour force at all. In our data, this concern is especially valid, as only 22% of the individuals get into paid employment (PSLM, 2014). The other source of selection bias is due to a very selected group of individuals who continue higher education in Punjab. This is especially worrisome for Pakistan, as the literacy levels are very low in the country. Amongst women in the age range of 15-65 years with at least a primary level of education, only 19% have acquired higher education (PSLM, 2014). If individuals' unobserved characteristics that lead them into paid employment or higher education also have implications for their wages, then these sources of selection bias need to be controlled for.

To tackle the problem of selection bias originating from these two sources, we make use of the Oaxaca Blinder methodology coupled with the Heckman (1979) selection correction method to correct for both selection biases. The other methodological concern is the endogeneity in educational attainment, which introduces endogeneity bias in the estimates of the wage equation. To account for endogeneity bias, we also make use of instrumental variables in our estimation of the gender wage gap using the Oaxaca Blinder technique.

Our basic estimating specification for measuring the gender wage gap is a human capital specification following Blau and Kahn (2017), where we control for education, experience, and region to observe the percentage contribution of the explained and the unexplained gap to the total gender wage gap. The real challenge here is to be able to pin down factors that may explain the source of the unexplained gap. To get around that we add to the base specification additional variables that when controlled for help to reduce the unexplained gap and increase the explained gap and thus allowing us to understand where is part of this unexplained gap coming from. To understand the source of this unexplained gap, we add to our basic human capital specification industry and occupation-specific gender ratios to see if some of this unexplained gap could be attributed to the nature of jobs men and women perform in the labour market.

The premise for adding the industry and occupation-specific gender ratios is a trend we noticed in the data, which is that approximately ninety percent of women with tertiary education in Punjab end up joining the 'Social and Personal Service Industry', and within this industry, there is a very narrow set of professions, i.e., health and education professionals (PSLM, 2014). What we argue in this chapter is that since women tend to concentrate in a very narrow set of professions and sectors, this excess supply of women in these jobs along with the lack of substitution between genders for these jobs can be a potential explanation for why women's wages are rising slower than men leading to a widening of the gender wage gap in Punjab.[2] In a model where we correct for selection into paid employment to estimate the gender wage gap, we additionally control for the industry- and occupation-specific gender ratios, the explained gap increases and the unexplained gap falls. However, when we also correct for selection into higher education using either the Heckman selection correction or IV methodology to correct for endogeneity bias, we obtain mixed results.

[2] men also enter these sectors and take up these job but in contrast to women they also join other professions such as engineers, lawyers, IT professional etc.

This chapter makes use of two rounds of the Pakistan Social and Living Standards Measurement data set for the years 2006 and 2014 to analyse the trend in the gender wage gap and its individual components. Over the years, while the gender gap has increased, the unexplained gap seems to have contributed much more than the explained gap. Adding the industry and occupation-specific gender ratios shrinks the unexplained gap (in the case of only correcting for selection into paid employment), but in magnitude, it still contributes much more to the gender wage gap than the endowment effect.

The third chapter examines returns to tertiary education and how those returns differ for men and women. An important puzzle that this paper seems to find an answer for is a trend in the data that shows substantial gender gaps in enrollments at the secondary and lower levels of education but a fall in this gap at the postsecondary level. Despite the reversal in the gender gap in enrollments from lower to higher levels of education, the gender gap in the labour market returns persists. This particular chapter, therefore, aims to estimate the gender gap in returns to tertiary education by using the instrumental variable technique using ‘the number of intermediate and graduate degree colleges at the district level in Punjab’ as an instrument. In an attempt to solve the problem of endogeneity that a Mincerian wage equation suffers from, this chapter also tries to get at a very important and policy-relevant question, as the first stage of IV regression lets us ask if an increase in physical capital leads to an increase in human capital.

The premise for using this IV for finding returns to tertiary education in Punjab again is the fact that enrollment of girls and boys in postgraduate and graduate classes in Punjab has increased from 2006-2014. There has also been an increase in the supply of these colleges over the same period. To be precise, the number of tertiary education institutes increased by 63% in the last decade from 2006 to 2014, whereas enrollment in these institutes increased by 51% in the same time frame (Punjab Development Statistics, 2014), making opportunities for acquiring higher education easily accessible for both men and women in terms of both affordability and distance. Indeed, we show in our first stage that an increase in colleges significantly increases the years of education attained beyond matriculation for both men and women.

What is puzzling about this finding is that if girls in large numbers are going to college to gain tertiary education why is the school-to-work transition not happening for them as is evident from a very low female labour force participation rate in Punjab? Of course, several constraints prevent them from entering the labour force, such as mobility, social norms, and employers' demands (Field et al., 2010; Heath and Mobarak, 2015; Field and Vyborny, 2016; Erten and Keskin, 2018; Jayachandran, 2020). However, if all of that is common knowledge, why do households invest in the human capital of these girls in the first place? The second stage of our analysis gives one plausible answer to that question, which is that although on average men earn higher than women, the marginal returns to acquiring one extra year of education beyond matriculation are higher for women than for men. It could be that the incremental benefit of gaining an additional year of education is higher for women, which motivates greater investment in girls' education beyond matriculation.

This particular chapter also makes use of the five rounds of PSLM data as were used for the previous chapter, but the data for instruments were from Punjab Development Statistics and Statistics of Arts and Science Intermediate and Degree colleges for the above stated years.[3]

Chapter 4 of this thesis aims to understand the impact of motivational nudges in the form of stories of role models on the job search efforts of women and their eventual entry into the labour force. The motivation for this chapter is the modest impact of

[3] This data is available on the Punjab Bureau of Statistics website. http://www.bos.gop.pk/ developmentstat

previously implemented high-cost job-search assistance and skills training programs. We conduct a randomized controlled trial with a sample of 2500 female undergraduate students going to 28 female public degree colleges in urban Lahore.

To a randomly selected one-half of this sample, we show a 10-minute motivational documentary based on the lives of five girls who are also graduates of these colleges and are now successfully employed in the labour markets followed by a brief discussion by the enumerator on the key message of the video.[4] We showcase the lives of graduates of these colleges to keep the role models relatable to these undergraduate students as they belong to similar socioeconomic backgrounds. The other half of the students in the placebo group were shown a video on a completely unrelated topic. We also tried to alleviate some external constraints by giving information regarding the job portal 'Job Asaan' to everyone in our sample. Job Asaan is a job-matching service that, in addition to bridging the information gap between employers and potential job candidates, also provides CV making and interview preparation services.

In doing this experiment, we hoped to determine whether a low-cost motivational nudge affects the job-search efforts of undergraduate students and their eventual entry into the labour force by encouraging a growth mindset. We estimate the effect of this intervention immediately after showing the documentary on the growth mindset and the absorption index. We indeed find that students in the treatment group immediately after watching the documentary show a higher growth mindset and tend to score higher on the absorption index. Since immediately after is a very short duration, we

[4] The discussion by enumerators emphasised to follow in the footstep of these role models who despite facing different challenges in their lives are now gainfully employed; therefore, we must learn that setbacks are an opportunity to learn; that the process of learning is enjoyable in itself; and that economic empowerment can help both their standing in the household and household welfare.

reinforced the key messages in the documentary four months after the baseline in a follow-up survey.

We collected high-frequency data for this group of students by performing three follow-up surveys over 18 months with a balanced sample of 1443 students. The effect of the motivational nudge does not last for long as we do not find any effects on work status or job search efforts at 9, 12, and 15 months. At the endline, 18 months after the intervention, however, we find that the treatment group is 4.7% more likely to be working. We find that this effect is predominantly driven by a subset of the sample who belonged to households where the income is low and parents' education levels are also very low in a heterogeneity analysis. The timeline for collecting endline data coincides with the start of the nationwide Covid lockdown. We, therefore, believe the effect at 18 months may have been driven by the stress of job and income loss due to lockdown, which was significantly higher in the low-income households.

The rest of this thesis is organized as follows. Chapter 2 examines the gender wage gap for Punjab using different wage decomposition techniques. Chapter 3 examines the returns to tertiary education and the gender gap in these returns. Chapter 4 looks at the findings of an RCT aimed to test the impact of a motivational nudge on job search e ort and female labour force entry. Chapter 5 concludes.

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2. Paper I: Too much of a good thing? Increasing gender wage disparity in the face of rapidly expanding postsecondary female education in Punjab, Pakistan

Introduction

While women in Punjab are catching up with men on prime human capital determinants, especially years of schooling, the gender wage gap does not show any signs of convergence. As paradoxical as it may seem, this paper aims to explore this puzzle to look for plausible explanations for the increasing gender wage gap in Punjab that extend beyond the traditional human capital determinants. Particularly, we explore labour supply increases as one of the plausible causes of the rise in the gender wage gap in Punjab. The FLFP rate of working-age women (15-65 years) with more than ten years of education is only 22.8 percent in Punjab (LFS, 2017). Moreover, these women are concentrated in only a handful of sectors and occupations. For instance, 95% of these women are employed in the health and education sectors of the 'Social and Personal Services industry' as health and educational professionals (PSLM, 2014). While women with higher education crowd only a few occupations and sectors, this may have some implications for how their wages trend over time. We argue that this can create pressure on wages to not rise at the same rate as men's wages are rising, particularly in these sectors and occupations with men and women not being perfectly substitutable for all jobs, thus widening the gender wage gap here. While men also enter the sectors and occupations that women are joining, there is a clear distinction that the fields that men join within these industries and occupations are very different from what women choose to join .

This paper, therefore, aims to understand the role of the excess supply of highly educated women in a handful of jobs in affecting the gender wage gap in Punjab. We hypothesize that when a vast majority of women compete for selected jobs, the wages that these vacancies have to offer tend to fall, thus widening the gender wage gap. We employ the traditional Oaxaca Blinder Methodology to first split the wage gap into explained and unexplained components. We then ask how the percentage contribution of each of these components is affected when we control for the sector-specific gender ratios (henceforth the supply effect) in our base specification. A change in the percentage contribution of each as a result of controlling for the supply effect can be taken as a sign that the selective nature of participation of women in the labour force does have a role to play in determining their wages and subsequently the gender wage gap. One potential concern here is that our selected variable to capture the supply effect is endogenous, as the wages available can also affect supply through entry into the labour force. However, this correlation is an equilibrium relationship, so the significance of the beta coefficient of the supply effect should be interpreted as the significance of this equilibrium relationship and not a causal one. The more appropriate method requires the use of an instrumental variable to account for this endogeneity.

The choice of our methodology for studying this research question is driven by concerns regarding selection bias since we are dealing with a very selected sample: highly educated individuals employed in paid work. If individuals' unobserved characteristics that lead them into paid employment also have implications for their wages, then this source of selection bias needs to be controlled for. Selection into higher education is especially worrisome in the Pakistani context, as literacy levels are very low in the country. Amongst men in the age range of 15-65 years with at least a primary level of education, only 17% have acquired higher education compared to 19% amongst women from the same cohort (PSLM 2006 & 2014). This is especially concerning for women whose representation in less than ten years of education is far below men, and out of these select few, those who continue to higher levels of education have to be very different from other women in terms of observed and unobserved attributes such as motivation, perseverance, and determination that help them land into higher education.

Due to the selection bias originating from two sources, we use the Oaxaca Blinder Methodology coupled with the Heckman (1979) selection correction method to correct for both selection biases. In our analysis, we use a source of unearned income and the number of children below the age of seven in the household as exclusion restrictions to correct for selection into paid employment following Asadullah,& Xiao (2019), Asadullah, (2006), and Duraisamy(2002), and we account for selection into higher education using parents' education levels as exclusion restriction learning from Méndez-Errico et al. (2019). However, since parental education cannot be determined for every individual in our sample, we use a rather crude measure, which is the average education level of the household, as our exclusion restriction.

The other methodological concern in this analysis is the endogeneity bias in educational attainment. Since one's innate ability tends to be correlated with both educational attainment and eventual earnings, we also attempt to correct for this endogeneity by using three instruments with separate specifications for educational attainment. One of the instruments that we employ to account for this endogeneity is the gender composition of the household (Butcher and Case, 1993). In addition to family size variables, we also use ‘average education levels of the household’ and the ‘education level of the household head’ as instruments in separate models to compare the results across models and see if the results we obtain are consistent and remain stable across various choices of instruments. Since we do not have data on parental education for everyone in the sample, we proxy for it with these instruments.

The results from our base model where only selection into paid work is corrected for show that the gender wage gap over the study period has increased and the source of that increase is the rise in the unexplained gap. However, when we control for the supply effect in our base model, the explained component of the gender wage gap increases, and the unexplained component, more commonly known as ‘gender discrimination’, falls, suggesting that the sector/profession-specific relative supply of women has some role to play in determining the gender wage gap. Correcting additionally for selection into higher education by Heckman selection and for endogeneity bias in educational attainment reduces the explained gap but widens the unexplained gap. We, therefore, interpret the gender wage gap in Punjab as a case of valuative discrimination as opposed to allocative discrimination (Petersen & Morgan, 1995).

The analysis exploring the gender wage gap across the wage distribution reveals evidence of a ‘sticky floor’ phenomenon in Punjab, which shows that income inequality between men and women is higher at the bottom of the wage distribution than at the top. Moreover, almost the entire increase in the gender wage gap over the study period has been due to the rise in inequality at the bottom. The wage gap has fallen at the top and the middle of the distribution. Regarding the source of this gap, gender discrimination (coefficient effect as opposed to the endowment effect) is the major contributor to wage inequality amounting to approximately three-fourths of the total wage gap, and this is true for both rounds of data. Across the wage distribution, the unexplained gap is highest at the bottom and falls as you move towards the top, a trend that is opposite to what was the case in 2006. Our other important result is that once the supply effect or the industry/occupation-specific ratio of men and women is controlled for, the unexplained part of the gender wage gap shrinks, the explained part increases, and this effect is most evident at the top of the wage distribution..

The analysis was conducted using the Pakistan and Social Living Standards Measurement (PSLM). using two rounds of the PSLM, i.e., 2006 and 2014 to allow analysis for almost a decade.

This study contributes to the literature by finding empirical evidence of the effect of the female labour supply on wages in Punjab's labour market. We hypothesize that the selective nature of female labour force participation in a handful of sectors in Punjab is making the wages of women rise slowly compared to those of men. To the best of our knowledge, no previous study on Pakistan links labour movements to the gender wage gap. The scope of all previous studies analysing the gender wage gap in Pakistan is limited to only finding the magnitude of the gap without delving deeper into the plausible explanations for it and then testing them empirically. Additionally, this work will be a contribution to the study of labour markets in Pakistan, as it focuses on individuals with tertiary education, which is still an understudied area in Pakistan. However, restricting the sample to highly educated individuals introduces a selection bias. This paper also adds to the literature on wage gap decomposition analysis by acknowledging the selection bias due to selection into higher education and correcting simultaneously for selection into paid employment (traditionally accounted for in the literature) and selection into higher education. We also incorporate into our study a discussion on what could be driving the gender wage gap by looking at the trend in decisions preceding employment and social barriers to female labour force entry that are equally important sources of gender inequality and have implications for subsequent labour market returns.

Such an analysis is important, as the returns to tertiary education as projected over the life cycle reflect the expectations that influence current student decisions to participate in higher education. If the returns are higher, there is a positive signal from the labour market, and it should effectively lead to greater investment in higher education. By pointing out the factor responsible for the gender age gap, this paper highlights the areas of the labour market that may need to be targeted to achieve gender equality. Only determining if there is a gender wage gap is not very helpful what is additionally required is to understand its very source.

Literature Review

Analysing the gender wage gap is important, as the gender wage gap is shown in the literature to negatively affect economic growth by reducing the output per capita in at least two ways (Cavalcanti and Tavares, 2016). First, the gender wage gap is a tax on the labour supply; when women are paid less, they perform less than their potential, thus decreasing output per capita. Second, when women are paid less, their opportunity cost of not working falls. This causes fertility rates to increase, thus reducing the output per capita. It is therefore policy-relevant to understand the likely sources of the gender wage gap to avoid its negative macro consequences.

There is quite some work done on the gender wage gap in Pakistan. However, there are a few shortcomings in the previous literature on Pakistan, as I explain below, leaving room for more rigorous work on this topic. First, the studies performed on Pakistan are mostly dated. For instance, Ashraf and Ashraf (1993) use HIES (1979, 1986) and employ a Mincerian wage equation to find the gender wage gap. Siddique et al. (1998) employ HIES to find the gender wage gap using Oaxaca decomposition, whereas Siddique (2006) looks at the gender wage gap in three districts, Karachi, Faisalabad, and Sialkot, for export-oriented industries. Nasir and Nazli (2000) use the Pakistan Integrated Household Survey for 1995-96 to study the gender wage gap using a Mincerian wage equation. Second, as mentioned, these studies make use of a simple Mincerian wage equation to determine the gender wage gap. Where decomposition techniques such as Oaxaca decomposition have been used, the study lacks relevance, as the period it covers is a long time ago. Third, these studies conducted a static analysis by looking at a single year, and none employed a pooled cross-section of multiple years. The only study that makes use of multiple rounds of a data source is Sabir and Aftab (2007). This analysis makes use of two rounds of LFS covering a decade, 1996-1997 and 2005-06, to examine the evolution of the gender wage gap using a quantile regression approach. However, their analysis is now about a decade old. Aslam (2009) is one of the most rigorous studies in this field that looks at the gender gaps in returns to education by using instrumental variables and fixed effects in a Mincerian Wage setting. She also compliments her analysis with the Oaxaca wage decomposition analysis. Her work, although rigorous, is also dated since it uses PIHS 2002. The results from all of these studies show a consistently significant gender wage gap in Pakistan’s labour market. These studies may differ in their scope with regard to the period used or the area/region covered, but they all provide evidence of a substantial gender wage gap, while some also point to the fact that an unexplained part of the gender wage gap contributes more to the total wage gap. However, none of these studies, to the best of our knowledge, try to delve deeper to explain the reasons for the gender wage gap, e.g., by incorporating hypothesized controls and showing that explained or unexplained gaps are affected as a result of their inclusion. While finding the gender wage gap is one thing, coming up with plausible explanations to explain that gap, especially the unexplained part of the gender wage gap, is what future research in this area should be heading towards. This is currently lacking in the literature on the gender wage gap in Pakistan.

In that regard, in this paper, we aim to understand the role of the excess supply of women in specific sectors in determining the gender wage gap and its components. The preferences of women in terms of job attributes have implications for their eventual payoffs. Flexibility in working hours, for instance, is a common preference for women given their expected gender roles. Goldin (2014) describes this as leading to a mismatch of preferences between some employers and employees. While women may place a high value on flexible hours, different firms bear different costs of providing this flexibility. Some jobs may require staying in for long hours, maintaining interpersonal relationships, adhering to deadlines, or doing very specific tasks that do not allow for substitutability in your absence. All of this makes it costly for an employer to provide flexibility in work hours. The higher this cost is, the greater the penalty for women seeking this flexibility.

Second, women may have to exit the workforce to take care of the home and family. This gives employers less incentive to invest in an employee's skill development, whose future decision regarding continuing working is highly uncertain (Altonji and Spletzer, 1991). There is a fear of wasting time, effort, and resources in training such an employee when they cannot reap the benefits of this investment. Lesser investment in their human capital both at home and the workplace (on-the-job training) limits women's choices of occupations to only those positions where the skill demand is not very high or their work prospects are not lowered because of deterioration of their skill set while they are away from the work life (Polachek, 1981).

Women may also have to face a 'Motherhood wage penalty' (a concept that embodies the negative relationship between the number of children and wages (Epstein, 1988; Neumark and Korenman 1992)) when they look for child-friendly jobs that naturally pay less or decrease their productivity, as they may put less effort at work or be reluctant to commit to demanding roles or rigorous work.

Different sectors also differ in terms of the skillset requirement and the ultimate return on these skills. Therefore, if men and women choose to join different sectors, then this can cause their wages to differ depending upon what skills are demanded by the sector they choose to work in and how that sector rewards that skill (Blau & Kahn, 1992). The increased influx of women in specific occupations has been shown in the literature to affect both the 'within occupation' and 'between occupation' gender wage gap. For instance, Levanon et al. (2009) show that a large influx of women into certain occupations significantly reduces the pay for those professions even when one accounts for the other human capital determinants. Goldin (2014) also documents the gender wage gap between and within sectors and occupations. This wage gap could be reflective of choices that women make in terms of going for jobs that allow them to maintain a work-life balance, as discussed previously. More than between-sectors (occupation), the within-sectors (occupations) wage gap is a serious concern, as it hurts the gender wage gap more. Research has shown that when women enter a sector in large numbers, the wages in that sector begin to fall, showing that the effect runs from changes in the supply of women to changes in average wages rather than wages affecting supply (i.e., women's entry into a job in large numbers reduces its pay rather than women entering low-paying jobs) (Blau and Kahn, 2017; Miller 2016).

Subject choices in the degree specialization are also an important determinant of one's earnings (Black et al. 2008), as these choices determine the occupational choices later in life. The wages of men and women may diverge because of the subject majors they choose to graduate in. This difference is also evident in the case of Pakistan; for instance, women are severely underrepresented in STEM (Sciences, Technology, Engineering, and Mathematical) fields (PCST, 2011). Approximately 70% of girls enrolling in higher secondary choose to enroll in nonstem fields (PCSW, 2018).

Basic economic theory teaches us that as labour supply increases, wages must fall. For instance, Ester Boserup (1970), in her influential work on India, proposes that the lower wages of women in the South could be due to higher female labour force participation rates there compared to women in the North. Her work was later confirmed by Mahajan and Ramaswami (2015), who find evidence of lower wages for women in the South, where women are well endowed with the skill set needed to thrive in the agricultural sector, as opposed to the North, where women lack these skills. This finding highlights the importance of labour supply in determining wages. Boserup's hypothesis of lower wages in the face of higher FLFP holds when a division of labour according to gender does not allow for there to be perfect substitutability between genders; for tasks, each of them performs in the labour market (Jacoby, 1991). This hypothesis is especially relevant to a traditional labour market such as Pakistan. Acemoglu (2004) also provides evidence of a causal link between female labour supply and the wage structure in the United States. During World War II, as men were mobilized to serve in the Armed forces with most of them deployed overseas, women in large numbers drew into the labour force with the result that female labour force participation increased significantly in the US, making wages of women rise slowly compared to those of men and thus widening the gender wage gap. Related evidence from Pakistan suggests that the wages of private school teachers are lower in villages that house a government girls' secondary school (Andrabi et al., 2007). Girls who pass out with secondary education from these schools add to the supply of school teachers who can teach at the primary level. This increased supply of primary school teachers in settings where women face limited mobility and few opportunities to work or gain further education leads to a decrease in the wages of primary school teachers.

Conceptual Framework

The intuition proposed in this paper, increase in female labour force participation lowers women's wages, emerges from Acemoglu (2004) which for a competitive labour market setting assumes three factors of production male workers, female workers, and physical capital all of which are imperfectly substitutable. Imagining a constant elasticity of substitution aggregate production function where the elasticity of substitution between labour and non-labour inputs is one and between men and women is greater than unity, the theoretical model developed shows the effect of an increase in female employment on men and women's wages while each is paid their marginal product. The results of this setting prove that given capital is fixed in the short run if men and women are assumed to be perfectly substitutable (elasticity of substitution approaches infinity) an increase in the female labour supply by lowering the capital to labour ratio lowers wages for both men and women. An increase in the labour supply with fixed capital reduces marginal productivity of labour the variable factor. But if the elasticity of substitution between men and women is lower than infinity or approaches zero then they behave as q-complements. The effect of a rise in female labour supply in this case on males' wages is positive while the opposite is true for women's wages. The extent of the fall in women's wages depends on the elasticity of substitution and the share of female labour cost in the total labour cost. As the cost of hiring women increases the negative impact of increasing female labour supply on women's wages increases as well.

This simplistic setting by Acemoglu (2004) thus shows that while capital remains fixed in the short run an increase in the female labour supply lowers the wages of women while the effect on men's wages is ambiguous and depends on the elasticity of substitution between men and women. If men and women engage in very different type of activities in the labour market or the one of them chooses to perform very narrow set of activities, then the elasticity of substitution between genders is very low and one should expect the wages of the more flexible gender to rise and those of the rigid one (in terms of their choices) to fall. However, if the extent of sorting in the labour market is low such that men and women readily substitute each other for the activities they perform then wages of both genders should fall as female labour supply increases.

This setting seems quite relevant for Pakistan where there is excessive sorting. We show later in tables 3 and 5 of our results section that women in Punjab's labour market choose to join a very narrow set of occupations and industries marking a low degree of substitutability between men and women. Therefore a priori our expectations are for women's wages to fall as their participation in the labour force in these particular sectors increases thus increasing the gender wage gap.

Methodology

To determine the gap in returns to tertiary education, this analysis makes use of the *Oaxaca–Blinder Decomposition (1973).* This method decomposes the gap into its explained and unexplained sources. In other words, it estimates what portion of the gender gap is due to discrimination as opposed to the observable differences between men and women. This is a very common method of finding the gender gap in any statistic. It decomposes the estimated gap into its explained and unexplained portions, where the explained portion of the gap is due to the observable differences between the two genders and the unexplained portion is a measure of discrimination.

The total gap between returns to tertiary education between men and women as computed by the Oaxaca methodology is as follows:

$$\boldsymbol{Gap = w(\overline{X_b}, \widehat{\beta}_b) - w(\overline{X_g}, \widehat{\beta}_g)} \qquad \textbf{.....2. 1}$$

where $w(\overline{X_b}, \hat{\beta}_b)$ is the predicted wages for boys (b) given their characteristics and $\overline{X_b}$ and $\hat{\beta}_b$ are the predicted coefficients of the wage equation. Similarly, $w(\bar{X}_g, \hat{\beta}_g)$ are the predicted wages of women given their characteristics and estimated wage equation coefficients. The decomposed components of the above-stated gap into an endowments effect and a coefficients effect using the Oaxaca Blinder methodology are as follows:

$$\boldsymbol{EXP = w(\overline{X_b}, \widehat{\beta}_g) - w(\overline{X_g}, \widehat{\beta}_g)} \quad \textbf{.....2. 2}$$

where the above-stated gap signifies the "endowment effect" and occurs due to group differences in the predictors. This is the explained portion of the gap. The second portion, which is the unexplained one, is called the "coefficient effect". It quantifies women's average wages if they had boys' coefficients:

$$\boldsymbol{UEXP = w(\overline{X_b}, \widehat{\beta}_g) - w(\overline{X_b}, \widehat{\beta}_b)} \quad \textbf{.....2. 3}$$

We estimate the OB model using two specifications: i) a base specification that controls for education level, years of experience, marital status, and region (the districts to which the wage earner belongs in Punjab); and ii) a full specification that, in addition to controlling for everything in the base specification, also controls for the industry, the professional category, and the industry and profession-specific gender ratios at the district level.[1] The reason for controlling for these gender ratios is to test for the supply effect, as discussed earlier. We hypothesize that once these ratios are controlled for, the explained part of the gender wage gap should increase, and the unexplained gap should fall. We expect this to be the case, as working-age women with higher education in Punjab tend to enter very specific sectors and professions, which may cause the wages of women to rise slowly in these sectors/professions, leading to an increase in the gender wage gap. We base our expectations on two indications from the data. First, approximately 95% of women enter the 'Social and Personal Services' industry as health and educational professionals, and second, when sector/occupation ranks (in terms of the number of

[1] I construct these ratios by dividing the total number of women in an industry/profession in a district by the total number of women in that industry/profession in that same district.

women who enter here) are plotted against the gender wage gap in these sectors/professions, one obtains a positively sloped line, which is suggestive of a positive correlation between the two series, as also shown later in Figures 4, 5, 6, and 7. However, one limitation that needs to be highlighted at the outset is that while we hypothesize labour supply to affect wages, it could be the other way around as well. The appropriate way of dealing with this endogeneity is to find an exogenous source of variation in the labour supply and use it as an instrument. However, this study does not account for it, and the relationship between labour supply and wages is at best a correlation; therefore, the results need to be interpreted with caution.

One drawback of the OB technique is that it focuses too much on the mean. It allows us to measure the average effect of an explanatory variable over the entire distribution of an outcome variable. There is now growing literature looking at wage differentials between subgroups that goes beyond simple mean comparisons and posits that there could be varying degrees of inequality at different levels of the wage distribution, for example, the ‘glass ceiling effect’, showing higher wage inequality at the top of wage distribution compared to at the bottom of the distribution. To get at it various econometric techniques are now available that allow for estimating the gender gap at different segments of the wage distribution or even along with the entire distribution. There are several approaches in the literature that allow the construction of counterfactual distribution at different points of the distribution of the covariates. This paper, therefore, makes use of the three different techniques for the estimation of the counterfactual wage distribution as robustness checks. The details of these techniques and the results based on those are available in Appendix A3.

Methodological concerns

The analysis of wage estimation using a simple Mincerian wage equation suffers from sample selectivity bias, as only those individuals who are part of the labour force and are earning nonzero wages are included in the sample. This is problematic when individuals who participate in some paid productive activity are very different from individuals who do not because of many observed and unobserved characteristics. Some obvious examples of these characteristics could be motivation, arduousness, risk aversion, negotiating ability, or even socioeconomic background. If a selective sample of men and women who enter as paid employees in the labour force have certain attributes that correlate both with their decision to enter paid employment and their subsequent wages, then a simple wage equation cannot give us the true impact of the observable characteristics.

The other concern that needs to be highlighted here is that we include in our analysis all those individuals who have acquired more than ten years of education. Given the very low enrollment rates of women in Punjab (we present the statistics for this later in the next section), a very restricted group of women have the privilege to go to school, and an even more selective sample subsequently enters into higher education. It can be argued that women who continue to higher education are very different from women who do not make it to college on account of their observable (family background, socioeconomic status, grades) and unobservable (grit, perseverance, motivation, determination) attributes. In that case, estimating a simple wage equation will lead to erroneous results if the nonrandom selection of individuals into higher education with personality traits that matter for their subsequent labour market returns is not accounted for.

These two characteristics make our sample highly selective, thus giving rise to selection bias. This nonrandom placement of highly educated individuals across different employment statuses, therefore, needs to be accounted for. In our analysis, we do this by relying on the two-step Heckman procedure (1979), as is traditionally done in the related literature. In our analysis correcting for sample selection bias, we deal with both types of selection biases mentioned above. We discuss below how we tackle each of the selection biases in our analysis.

We use the Heckman (1979) model to estimate our wage function free of selection bias. To correct for the nonrandom selection of individuals into paid employment, we first estimate a probit regression of participation into paid employment on all the variables included in the full specification in the simple wage decomposition analysis in addition to an exclusion restriction. Using this probit regression, we estimate lambda, the selection correction term, and then later use it as an extra variable in our wage function to account for selection. The exclusion restriction we use in our probit regression for participation in paid employment is ‘assets’ that households possess to control for a source of nonlabour income. In choosing this exclusion restriction, we follow Asadullah (2019), Asadullah (2006), Aslam (2009), and Duraisamy (2002). We use assets as they are an indirect proxy for nonlabour income. A direct proxy of nonlabour income would constitute proceeds from the sale of assets or income received from land, rents, lotteries, or remittances (Asadullah, 2006). Since in our data using the income received from bequests is not possible as there are many missing values, we restrict ourselves to controlling for a household's possession of a certain asset only as indirect proxies of nonlabour income. The assets that we control are agricultural land, commercial buildings, residential buildings, livestock, animal transport, and poultry. The other exclusion restriction we use is the number of children below the age of seven in the household to also allow for the fact that women must be available at home to take care of household chores, making it difficult for them to participate in the workforce. All these measures are expected to affect the decision to participate in paid employment, as these assets can be a source of generating income for the households, thus increasing the probability of the household indulging in self-employment but do not directly affect one's labour market earnings.

To account for selection into higher education, we use parental education as an exclusion restriction in a separate Heckman model where the outcome function is the years of education. This exclusion restriction works in our case, as the literature does show that long-term factors such as parental background and ethnicity tend to matter at every level of education, whereas short-term factors such as family income do not seem to matter much, especially at higher levels of education (Méndez-Errico et al., 2019). Our selection function here is a probit regression of a binary indicator of having acquired more than ten years of education using parental education as an exclusion restriction. From this Heckman analysis, we compute the estimated years of education from the outcome function and later use these estimated years of education in our wage equation to correct for selection into higher education.[2]

[2] It is important to mention here that in our data, there are very few individuals for whom parental education can be identified we, therefore, also use the average education level of the members in the household excluding individual 'i', as another exclusion restriction.

This analysis is also prone to an endogeneity bias that arises due to unobserved innate ability jointly affecting one's educational attainment and the wages earned in the labour market. We address this endogeneity bias by using the instrumental variable technique. There are many instruments that researchers have made use of to address this endogeneity. Our data do not allow us a very rich set of indicators to use those instruments. We, therefore, use 'average education level of the household' and 'education level of the household head' as instruments to correct for endogeneity bias in educational attainment. Although parental education (Asadullah, 2019; Mishra and Smyth 2013; Heckman and Li 2004) would have been a much better instrument, due to a very small number of individuals for whom this information can be obtained from the survey, we have not used it as an instrument. We take the education level of the household head as a proxy for parental education. A highly educated household head could also have a positive impact on the educational attainment of other household members. The 'average level of education of the household' is also a suitable instrument, as it does not influence an individual's innate ability but can have an effect on their educational attainment. For instance, if parents and siblings have a higher level of educational attainment, there is a higher chance that this person will also have more years of education attained.

We also used the gender composition of the household, more specifically the number of female and male individuals in the household, as an instrument for years of education following Butcher and Case (1993) to analyse the impact of siblings' gender composition on educational attainment. They provide sufficient evidence in their work to suggest that women who have a greater number of sisters tend to have lower educational attainment compared to families where the same number of men are present. Jensen (2002) argues that in families where there are a greater number of girls, educational outcomes generally suffer because of sons' preferring fertility behavior of parents that increases the family size, thus leaving fewer resources per head available to be spent on education. The gender composition of the household is a suitable instrument, as families with a greater number of girls are typically large, and relevant literature has argued that family size or birth order does not have a direct effect on one's earnings (Björklund and Jäntti, 2012; Kessler, 1991; Behrman and Taubman, 1986). There is another strand of literature that also shows that later borns (which also means larger family size) have lower educational attainment (Bagger et al., 2013; Björklund and Jantti, 2012; De Haan, 2010; Kantarevic and Mechoulan, 2005).

We use the demand-side instruments as sources of exogenous variation in educational attainment. However, the demand side instruments are criticized in the literature on account of the intergenerational transmission of ability that may affect the productivity of family members such as parents or siblings and oneself similarly (Björklund and Salvanes, 2011; Chavalier et al, 2013, Dickson and Smith 1995). Moreover, the mechanism of this intergenerational transmission is not clear. For instance, in the case of the effect of parental education on one's educational attainment, it is difficult to establish if the effect is due to genetic transfer or other environmental factors, such as the quality of life that educated parents can provide to their children. If it is the latter, then it is simply the parental income that plays a role, but if it is the former, then a causal effect is difficult to establish (Björklund and Salvanes, 2011). Similarly, in the case of average education of the household, which includes spousal education as well, a possible source of endogeneity is the marriage matching decision, where the educational attainment of one's spouse may have affected the choice of partner. Therefore, given all these endogenous factors, we need to interpret the results with caution. Our data do not allow for a very rich set of supply-side exogenous instruments; therefore, we are restricted in our choice of instruments.

For our empirical analysis, we first perform wage decomposition analysis correcting for only selection into paid employment. We use this as our base model and compare the results from other models with it. We call it Model 1 (Table 2.6). Every time selection into paid employment is corrected for the 'sources of nonlabour income'/bequests, and the number of children below the age of seven in the household is taken as exclusion restrictions along with the 'total number of children in the household below the age of seven'.

We also correct for selection into higher education in addition to correcting for selection into paid employment in Model 2. We run three variants of Model 2. In Model 2a, 'average education level of the household' is used as the exclusion restriction for correcting for selection into higher education (Table 2.7). To correct for selection into higher education, we estimate a separate Heckman model[3] and use the estimated years of education from this model in place of the actual years of education in our wage equation. We compare the results of Model 2a with another model run for a subsample for whom parental education is available to use parental education as an exclusion restriction. We do not present the results of this model in the main text but include them in Appendix A1 at the end (Table A1).

[3] For this model our outcome uses years of education as the dependent variable and the selection function uses a dummy for having completed more than ten years of education as the dependent variable. The exclusion restriction used here is the 'average education of the household'.

In Model 2b, we also attempt to correct for endogeneity bias in educational attainment in addition to correcting for selection into paid employment. We achieve this by using the ‘education level of the household head’ as an instrument. while also correcting for selection into paid employment (Table 2.8). In Model 2c, we use ‘gender composition of the household’ as an instrument instead (Table 2.9).

Data and the Descriptive Statistics

The analysis makes use of two rounds of PSLM for the years 2006 and 2014 to study the trend in the wage gap for almost a decade. The total number of individuals with higher education in our sample in the working-age range of 15-65 years is 67,896 in 2006 and 70,580 in 2014. Approximately 23 percent of individuals in each of these rounds are into paid employment, with the remaining split between ‘self-employment’ and ‘not working’. Table 2.1 below shows the breakdown of our sample into three categories of work status. The breakdown of these categories by gender additionally shows how so many women are not even a part of the workforce compared to men making working women a very selected sample. Pakistan has a very low female labour force participation rate because of the many barriers they have to face to work. Some commonly cited barriers include mobility, home care, social norms, sexual harassment, and many others together make it very difficult for women to come out of the house and earn a livelihood[4].

We run our analysis of estimating the gender wage gap on a subsample of these individuals who are into paid employment and have acquired more than ten years of education. This subsample for 2006 has 3656 individuals with 731 women and 2,925

[4] We present a detailed discussion on some of these in Section 8.

men, and for 2014, this subsample includes 3369 individuals with 882 women and 2,487 men. This is a brief snapshot of the data used for estimating the gender wage gap. Table 2.2 shows that in both years, men in our sample are on average older, have more years of experience, and earn more than women[5]. However, the difference between the highest education level attained between men and women is higher in favor of women. All of these differences between men and women are significant at all levels of significance, as shown by the t values of difference in the means test.

Table 2. 1 Distribution of sample individuals (aged 19–65 years) by work status

	Full Sample			More than 10 years of education		
	Year: 2006					
	(1) Total	(2) Male	(3) Female	(4) Total	(5) Male	(6) Female
Paid Employment	15459	13774	1685	3656	2925	731
	(23%)	(34%)	(6%)	(30%)	(42%)	(14%)
Self-Employment	12895	12362	533	1852	1759	93
	(19%)	(31%)	(2%)	(15%)	(25%)	(2%)
Not working	39542	14378	25164	6868	2291	4577
	(58%)	(35%)	(92%)	(55%)	(33%)	(85%)
Total	67896	40514	27382	12376	6975	5401
	Year: 2014					
Paid Employment	15248	13363	1885	3369	2487	882
	(22%)	(32%)	(6%)	(28%)	(39%)	(16%)
Self-Employment	13976	13023	953	1616	1485	131
	(20%)	(32%)	(3%)	(14%)	(24%)	(2%)
Not working	41356	14902	26454	6975	2325	4650
	(59%)	(36%)	(90%)	(58%)	(37%)	(82%)
Total	70580	41288	29292	11960	6297	5663

Note: Author's calculations using PSLM 2006 and 2014. This table is created for individuals who are in the working-age population of 15-65 yrs. Each cell shows the number of individuals in that

[5] Our measure of wages is log of daily wages that we compute by dividing the total income earned in the last month by the days worked last month. Each of these measures are available directly in PSLM.

category of employment. The percentages below each cell are the proportion of that category of the column total. Paid employment is all individuals who are paid employees. Self-employment includes individuals who are self-employed in the agricultural or nonagricultural sector. Not working are all individuals within this age bracket who are not employed.

As shown in Table 2.2, men in our sample on average earn significantly more than women, and the same phenomenon is evident in the kernel density graph shown below in Figure 2.1. A look at the raw data in figure 1 below clearly suggests that the distribution of daily wages for males for different levels of education is higher than the mean compared to the respective distributions of women who have a much more dispersed distribution and wages of a lot of them tend to concentrate below the mean for the full sample.

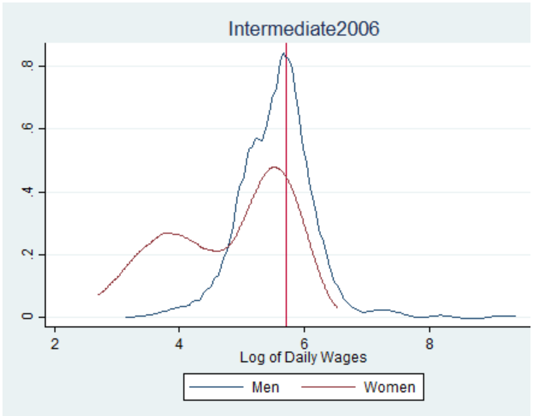
Table 2. 2 Means of Selected Controls by Gender

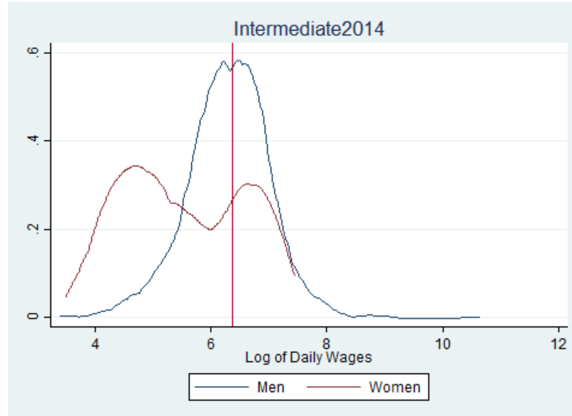
	Year: 2006			
	(1)	(2)	(3)	(4)
Variable	Female	Male	Difference	Count
Age (yrs)	29.65	35.919	6.270***	3,656
	(8.359)	(10.566)		
Years of experience(yrs)	11.33	18.105	6.732***	3,656
	(8.337)	(10.616)		
Years of education	13.309	12.829	-0.480***	3,656
	(2.552)	(2.38)2		
Real daily wages	304.098	487.613	183.515***	3,649
	(1.004)	(0.754)		
Observations	731	2,925		3,656
	Year: 2014			
Age (yrs)	30.686	36.026	5.340***	3,369
	(9.21)	(10.702)		
Years of experience(yrs)	12.429	17.969	5.540***	3,369
	(9.265)	(10.688)		
Years of education	13.282	13.065	-0.218***	3,369
	(1.355)	(1.496)		
Real daily wages	237.028	392.493	155.465***	3,362
	(1.016)	(0.741)		

Observations	882	2,487	3,369

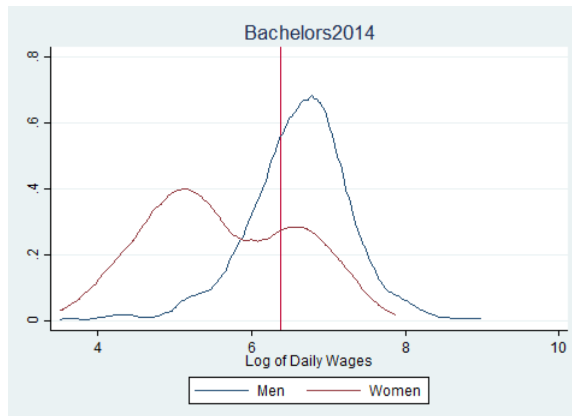
Note*:* Author’s calculations using two rounds of PSLM, 2006 and 2014. ‘Real daily wages’ are computed by dividing nominal daily wages by the CPI index for that year. We have used 2006 as the base year. The CPI index values were taken from the World Bank database. We computed nominal daily wages by dividing the total income earned in the last month by the days worked last month. ‘Experience’ is calculated as age-years of education attained-5 following Aslam (2009).

Another important finding from these density distributions is that the distribution of wages of women for both years for any level of education is bimodal. This indicates that women are either concentrated at the top or the bottom of their wage distribution. Men’s wages on the other hand follow a normal distribution. Additionally, for 2014, the first peak of women’s distribution is higher than the second peak at the intermediate and bachelor's levels. which points to many of them earning very low wages compared to men with the same level of education. Although this trend seems to have emerged only recently, as clearly in 2006, the second peak was higher than the first peak. Only at the master’s level do distributions of men and women tend to look similar in 2006, but in 2014, the women’s distribution turns bimodal, although the second peak occurs above the mean, but at the level of wages where the first peak occurs, there are many more women than men. This again shows that even for this level of education, men tend to earn more, and women tend to be concentrated in jobs that pay them less. Thus, the raw data indicate a gender gap in wages of men and women who have acquired more than ten years of education. Additionally, the three findings discussed above suggest that the gender wage gap has persisted over these years and may have even widened, as previously at least at the master’s level, men and women had similar distributions, but in 2014, the shape of women’s distribution looks like their distribution in 2006 at the intermediate and bachelor’s levels.


Intermediate2006
Log of Daily Wages
Men
Women


Intermediate2014
Log of Daily Wages
Men
Women


Bachelors2006
Log of Daily Wages
Men
Women


Bachelors2014
Log of Daily Wages
Men
Women


Masters and Above2006
Log of Monthly Wages
Men
Women

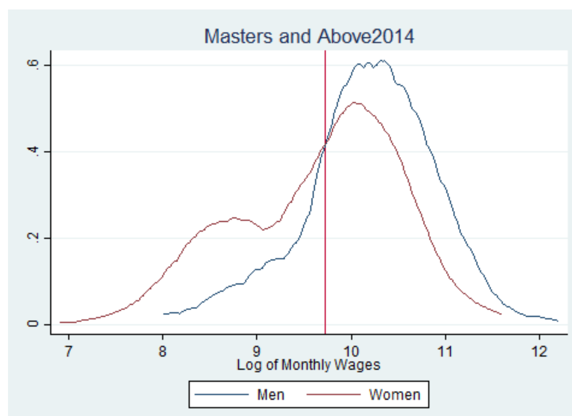

Masters and Above2014
Log of Monthly Wages
Men
Women

Figure 2. 1 Wage Densities by Education for Men and Women for 2006 and 2014.

To explore what could be a likely cause of this gender wage gap, the rest of this section presents the trends in the various determinants of wages for men and women. Since the most important determinant of wages is human capital, Figure 2.2 shows the trend in enrollment rates[10] of men and women at two levels of education, 'secondary and lower', which includes primary middle and matric, and the 'post-secondary' level, which includes intermediate, bachelors and masters. The enrollment rates of women in the postsecondary education levels have increased over time, and the subsequent gender gap in the enrollment rates at this level has also fallen. While the enrollment rates of women for secondary and lower education levels have stayed virtually constant, so has the gender gap in these enrollment rates.

Figure 2. 2 Enrollment rates of women and the gender gap in the enrolment rates at the secondary and lower level and postsecondary level of education across years in Punjab

[10] Enrollment rate of men(wome) at an education level is number of men (women) within the age range of 14 to 65 years whose highest level of education attained is that level of education, as propotion of total number of individuals in this age range.

Note: This figure shows the enrollment rates of females and the gender gap in enrollment rates in Punjab at secondary and lower levels and postsecondary levels of education in the years 2006 (blue) and 2014 (red). For the secondary and lower levels, we added the enrolment rates at primary, middle, and matric. For postsecondary, we added up the enrolment at intermediate, bachelor's, and master's levels. Two rounds of PSLM, i.e., 2006 and 2014 were used to make this graph.

This figure, therefore, shows that between 2006 and 2014, there was an expansion in postsecondary educational attainment for women that helped them catch up with boys in terms of a prime human capital determinant. In Figure 2.3, we divide the enrolment rates for each level of education beyond matriculation. One can see that most improvement for women has happened at the bachelor's level, where the gender gap is actually in favor of women (negative). At the other two levels, there has also been improvement, as the gender gap in enrolment rates at those two levels is also falling.

Figure 2. 3 Enrollment rates of men and women at the different postsecondary levels of education across years in Punjab

Note: This figure shows the enrollment rates of men and women in Punjab at the intermediate bachelor's and master's levels of education in 2006 (blue) and 2014 (red). Two rounds of PSLM, i.e., 2006 and 2014 were used to make this graph.

While the gender gap in enrolment rates at the postsecondary level has been on the rise for women, leading to a fall in the gender gap in postsecondary educational attainment from the supply side, there has been a simultaneous rise in the supply of educational institutions as well. In Table 2.3, we compare the growth of educational institutes for women and men at the postsecondary and secondary and lower levels. Two things are evident from this table. First, there has been a fall in the secondary and lower educational institutes for both men and women. However, this decline has been faster for men than for women. Second, the postsecondary educational institutes have been increasing n Punjab, and this growth is higher for women' educational institutes than for men. So where the postsecondary educational enrollment of girls is rising as shown in figure 2.3 this has been accompanied by a simultaneous rise in the supply of educational institutes in Punjab for women.

Table 2. 3 Number of secondary and lower and postsecondary educational institutes in Punjab by gender: 2006-2014

	Secondary and lower		Post-Secondary	
	(1)	(2)	(3)	(4)
Year	Women	Men	Women	Men
2006	28712	27470	333	339
2014	26243	24576	509	506

Note: This table shows the number of educational institutes in Punjab at the secondary and postsecondary educational levels. These data were taken from the Punjab Development Statistics for 2015.

With the gender gap in enrollment rates, especially beyond matriculation, having fallen and the gender gap in years of experience having fallen by one year, as shown in Table 2.2, there is an indication that women in Punjab are starting to get closer to men in terms of the human capital determinants. What therefore could be other reasons that may have caused the gender wage gap to increase over these years as shown in Table 2.2 as well. One possible explanation could be the excess supply of women in specific sectors and jobs. Although FLFP is very low in Punjab, when women enter the labour force, the data suggest that they tend to enter very selective jobs and sectors, as shown in Tables 2.4 and 2.5.

Table 2. 4 Distribution of Men and Women Across Industries: 2006-2014

	(1)	(2)
Year	Male	Female
Social & personal services industry		
2006	55.21	85.50
2014	51.72	95.39
Other Industries		
2006	44.79	14.50
2014	48.28	4.61

Note: *Other industries include agriculture, mining, manufacturing, electricity, construction, wholesale & retail trade, transport, and real estate

One can see that a major proportion of women (85% in 2006 and 95% in 2014) are employed in the ‘Social and personal services’ industry compared to men who are split half and half between this and other sectors. Within this sector, the majority of women are concentrated in the ‘Education’ and ‘Health’ sectors. Similarly, across different professional categories, women, as shown in Table 2.5, are mostly employed as health and educational professionals, such as teachers or nurses and doctors. As shown, there is a significantly higher proportion of men in Managerial jobs, which are considered to be high-level jobs that demand highly skilled and highly productive workers. On the other hand, women’s representation in professional jobs, which again demand high skill levels and commitment from workers, has increased. In 2006, the sample of women was split half and half between professionals and other categories, with very few of them employed in managerial positions. By 2014, we find almost the entire sample employed as professionals and only a handful of them in other job categories. Men, however, are dispersed across all occupational categories. This finding again points to the fact that as the human capital of women is improving, their employment opportunities are also improving in the sense that there is an increasing incidence of them working as ‘professionals’, who are relatively high-skilled jobs.

Table 2. 5 Distribution of Men and Women Across Professions: 2006-2014

Year	(1) Male	(2) Female
Managers		
2006	14.12	5.06
2014	8.47	1.49
Professionals		
2006	22.56	49.11
2014	32.71	89.33
Other professions*		
2006	63.32	45.83
2014	58.82	9.18

Note: This table shows the percentage of men and women in respective professional categories in 2006 and 2014. The categorization of professions follows the Pakistan Standard Classification of Occupations at the one-digit level.
*Other professions include technicians and associate professionals, clerical support staff, service and sales workers, skilled agricultural and fishery workers, craft and related trade workers, plant and machine operators and assemblers, elementary occupations

While women do crowd only a very limited set of jobs, in this paper, we argue that the excess supply of women in these selected jobs may be causing their wages to rise slowly compared to those of men, especially when men and women are imperfect substitutes for these jobs given women tend to prefer jobs that suit their gender roles and may find it hard to enter other jobs that are more demanding. To test this proposition of the “within occupation” gender wage gap, we take the number of women who enter a given professional category and rank them such that the profession with the most women is ranked 1. We plot this rank against the gender wage gap in that professional category for both rounds of data. A simple correlational analysis, as shown in Figure 2.3, depicts a downwards sloping line, which means that as the number of women entering a profession increases, the gender wage gap in that profession also increases.

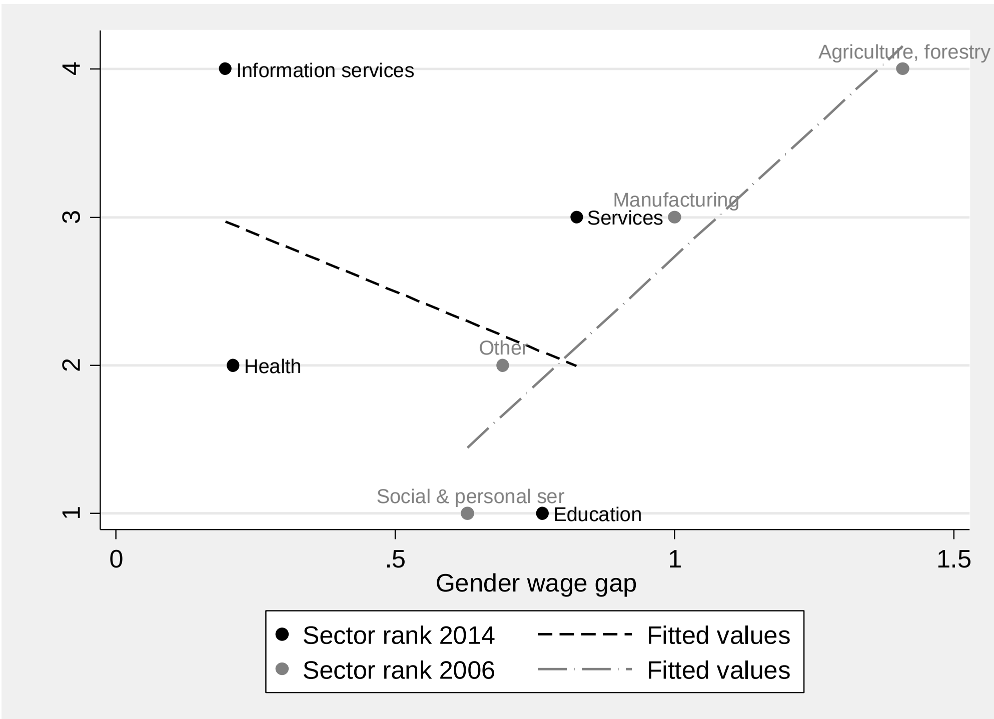


Figure 2. 4 Scatter plot of the gender wage gap and occupation rank

Note: This figure shows the scatter plot of the gender wage gap in an occupational category plotted against the rank of that occupation in terms of the number of females who enter that occupation. The occupation where the greatest number of females entered is ranked 1, and the occupation where the least number of women enter is ranked the highest.

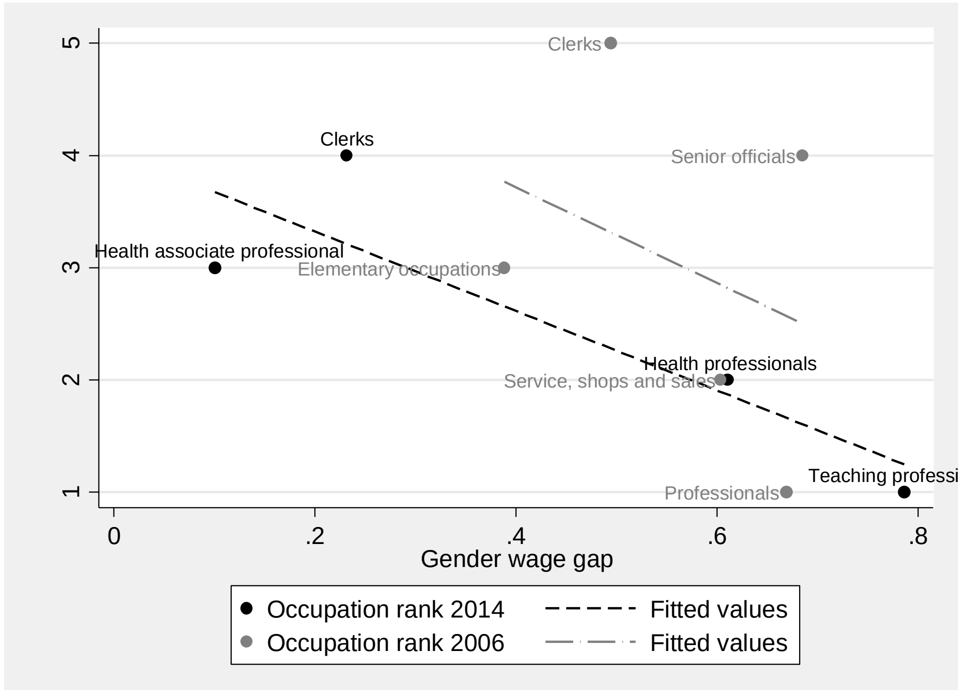


Figure 2. 5 Scatter plot of the gender wage gap and sector

Note: This figure shows the scatter plot of the gender wage gap in a sector plotted against the rank of that sector in terms of the number of females who enter that sector. The sector where the greatest number of females entered is ranked 1, and the sector where the least number of women enter is ranked the highest.

We also perform a similar analysis for sector categories by plotting the rank of every sector against the gender wage gap in that sector. Here, again, the sector with the greatest number of women is ranked 1. The resulting best fit line is again a negatively sloped line showing that as the supply of women in a sector increases, the gender wage gap in that sector increases. Although this effect is much stronger for 2014 than in 2006 as opposed to professional categories, in both years, the downwards sloping line is evident.

To present evidence of the “between sectors” and “between occupations” gender wage gap, we also plot the sector and occupation rank against the average wages in that sector to demonstrate that sectors and occupations where women enter in large numbers also have lower wages on average (Goldin 2014). Again, in the case of sectors ‘between sector', the effect is not very strong for 2006, but for 2014, one can see a positively sloped line indicating a lower log of daily wages in sectors where many women enter.

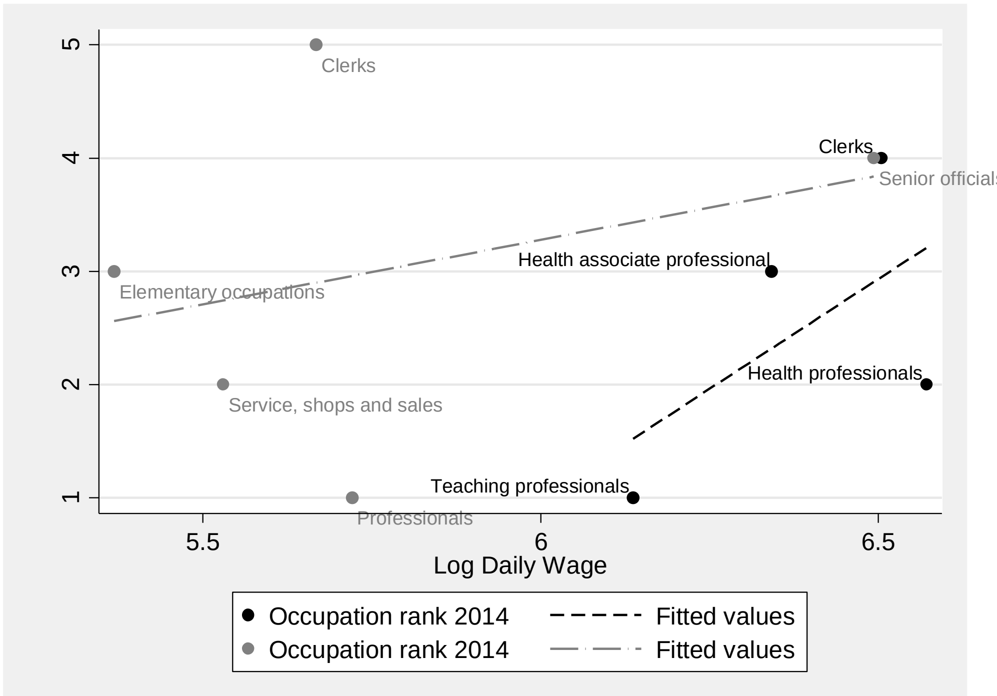


Figure 2. 6 Scatter plot of the log daily wages in occupation and occupation rank

Note: This figure shows the scatter plot of log daily wages in an occupational category plotted against the rank of that occupation in terms of the number of females who enter that occupation. The occupation where the greatest number of females entered is ranked 1, and the occupation where the least number of women enter is ranked the highest.

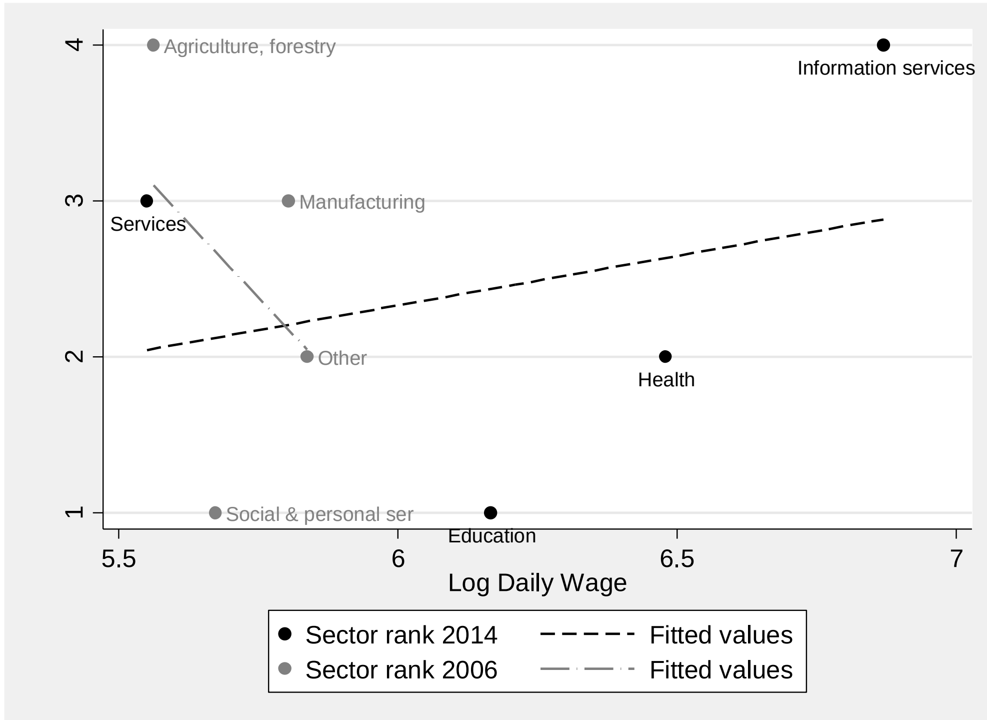


Figure 2. 7 Scatter plot of the log daily wages in a sector and sector rank

Note: This figure shows the scatter plot of log daily wages in a sector plotted against the rank of that sector in terms of the number of females who enter that sector. The sector where the greatest number of females entered is ranked 1, and the sector where the least number of women enter is ranked the highest.

Despite education and experience being the prime determinants of human capital and therefore of earnings and women demonstrating improvements in their human capital, the gender wage gap shows no sign of convergence. Men's wages are significantly higher than those of women for both years included in the analysis. While we are trying to explain the possible causes of the gender wage gap, trends in the most important determinants of one's earnings do not help much to narrow down the list of possible causes. Therefore, in the next section, we empirically test for the significance of these human capital indicators along with the labour supply effect in determining the gender wage gap using the traditional Oaxaca Blinder methodology. To confirm our results, we also present the analysis using other competing methodologies that have been developed more recently to estimate the gender wage gap and decompose it into its likely sources, both explained and unexplained, as tests of robustness later on.

Empirical Estimation of Gender Wage Gap using Decomposition Techniques

The remaining analysis is all about trying to understand where is this gap in wages mostly originating from by employing various decomposition techniques.

Estimation of Gender Gap at the Mean correcting for selection into paid employment (Model 1)

Table 2.6 shows the results of wage decomposition when only selection bias due to paid employment is corrected (Model 1). The decomposition performed in panel A represents the detailed decomposition analysis for 2006 and 2014 for a base specification where only education, experience, and the region variables are used as determinants of one's earnings. The entries in the first column for each represent the coefficient estimates, and the second column represents the percentage contribution of each determinant in the total wage gap. The decomposition performed in panel B represents detailed composition for 2006 and 2014 for the full specification where occupation and sector-specific gender ratios and industry and profession variables are additionally controlled.

The first and foremost finding from this table is that the gender wage gap over this period has risen. The total wage gap, as seen in Table 2.6, increases from 0.625 in 2006 to 0.689 in 2014. The findings for the base specification for the year 2006 suggest that the 'coefficient effect' or the unexplained part of the gender wage gap is much higher than the 'endowment effect' or the explained part. Its percentage contribution to the total wage gap is 71% compared to the contribution of the explained part of only 29%, which was further reduced to 22% by 2014. The highest contributor to the explained gap in the base specification in both the years is the years of experience, followed by region and marital status.

Education level, on the other hand, has a negative effect on the gender wage gap. This finding highlights how the increased enrollment of women in the postsecondary education levels may have helped them achieve higher returns in the labour market, contributing to a reduction in the explained gender wage gap. Despite the improvement in human capital and its subsequent favorable impact on the gender wage gap, the effect of other factors, especially those that contribute to the unexplained gap, has been so large that over time, the gender wage gap has increased rather than fallen.

Table 2. 6 Decomposition of the gender wage gap adjusted for selection into paid work (Model 1)

Year	**2006**		**2014**	
	Contribution of Explanatory Variables to Gender Gap		Contribution of Explanatory Variables to Gender Gap	
Variable	**Coefficients**	**Percentage of Gap**	**Coefficients**	**Percentage of Gap**
Panel A: Base Specification				
Education	-0.05	-8%	-0.056	-8%
Experience	0.171	27%	0.181	26%
Married	0.014	2%	0.008	1%
Region	0.044	7%	0.019	3%
Explained Gap	0.179	29%	0.15	22%
Unexplained Gap	0.446	71%	0.538	78%
Total Wage Gap	0.625	100%	0.689	100%
Panel B: Full Specification				
Education	-0.042	-7%	-0.048	-7%
Experience	0.156	26%	0.168	24%

Married	0.013	2%	0.008	1%
Gender ratio: Professions	0.03	5%	-0.031	-4%
Gender ratio: Industry	-0.035	-6%	0.04	6%
Region	0.032	5%	0.016	2%
Industry	0.024	4%	0.003	1%
Profession	0.005	1%	0.029	4%
Explained Gap	0.185	31%	0.186	27%
Unexplained Gap	0.417	69%	0.504	73%
Total Wage Gap	0.602	100%	0.69	100%

Note: This table shows the decomposition of the gender wage gap into explained and unexplained parts correcting for selection bias using Oaxaca Blinder Methodology with Heckman two-step procedure for the years 2006 and 2014 using PSLM. The selection bias corrected for here is the selection into paid employment using the household's possession of assets (Asadullah, 2019)) such as agricultural land, commercial building, poultry, livestock, residential building, and animal transport and the number of children below the age of seven in the household as the exclusion restrictions. The results of the selection function for each of these specifications are given in Appendix A2 (Table A21).

The next step from the results obtained in panel A in Table 2.6 was to look for other potential determinants that may help to pin down some factors that may be added to the unexplained gap. To look for the potential explanations for the unexplained gender wage gap, we returned to our raw data to see how men and women are distributed in the workforce (Tables 2.4 and 2.5). Essentially, we aim to determine what professions and industries men and women choose to work in, as this tells a lot about the preferences of men and women for the kinds of jobs they want to do and the kind of commitment they have towards work.

As jobs differ in terms of the hours of committed work, manual labour requirements, training, maintaining interpersonal relationships, meeting deadlines, etc., all of these requirements come together to shape a specific job, and depending upon what a particular individual can deliver on each of these dimensions would determine how individuals are sorted across different jobs. Now, as we have shown previously in Tables

2.4 and 2.5, men and women differ significantly in terms of their distribution across various occupations and sectors. Women, for instance, in our sample are increasingly found to be concentrated in one category, i.e., ‘Professionals’. This could be an indication of sorting taking place in the labour market because men and women having different preferences for job attributes make them land in very different occupational categories. The same is true for industries, as shown in Table 2.5. Almost all women in our sample are located in the ‘Social & Personal Services’ industry. Their participation in this industry has increased from 85% in 2006 to 95% in 2014. This again is an indication of excessive sorting occurring in the labour market.

Because these industries and occupations differ in terms of the payoff to the workers, this can have implications for the gender wage gap (Blau & Kahn, 2000). That is why in panel B of Table 2.6 we additionally control for industry and professions variables. Given that there is excessive sorting in the labour market, we hypothesize that the excess supply of women in selected professions and industries may cause their wages to not rise as fast as the men’s wages are rising in these sectors and occupations, thereby widening the gender wage gap. To test for this supply effect, we additionally control for the district-specific profession and occupation wise gender ratios. These gender ratios are measured by taking the ratio of men and women in an industry or occupation in a particular year for a district.

The results in panel B of Table 2..6 show that when industry, occupation, and their respective gender ratios are controlled for, the explained gap increases, accounting for 27% of the gender wage gap in 2014 and 31% in 2006. However, the unexplained effect falls from 78% in the base specification to 73% in the full specification in 2014.

Similarly, the contribution of the unexplained gap to the total gender wage gap falls from 71% in the base specification to 69% in the full specification for the year 2006. The combined contribution of education, experience, and marital status is 21% in 2006 and 19% in 2014 both in the base and the full specification. However, in 2014, this falls by one percentage point from 22% to 21% as we control for the supply effect. The contribution of the region has fallen in both years as we control for the supply effect, and some of its effects have been redistributed toward the industry and occupation variables, making their combined effect four percent of the total wage gap in 2006 and six percent in 2014. This finding points to the significance of the industry/occupation and the sorting of men and women across these for the gender wage gap. After controlling for these, we can see that there is some portion of the gender wage gap that was previously unexplained, which can now be explained by these supply-side effects of the labour market. Figures 4 and 5, which we presented previously, also confirm these findings by showing that the gender wage gap each year increases with the sector/occupation rank in terms of the number of females who enter that sector/occupation. Only for 2006 in Figure 5 do we see an upwards-sloping line that runs contrary to our expectations.

Within the broader category of 'professional' occupation, men and women choose very different fields. A closer look at the detailed distribution of occupations shows that within the professional category where women are mostly employed as health and educational professionals, such as doctors, nurses, midwives, or preprimary, primary, secondary, or university teachers, men, in addition to working as medical practitioners or educationalists, are also found in other occupational categories, such as engineers, business professionals, IT professionals or lawyers. Therefore, there is much more variety in occupations that men get to choose from, but for women, the spectrum is limited. This might be again because of the preferences of women for certain job attributes, such as flexibility in hours, safety, low skill demand, and lower demand for on-the-job training that most of the above-listed jobs are attributed to. The preferences of men and women, as the literature also suggests, may be related to their gender roles. As women are expected to be primary caretakers of the home, there is a greater need for them to maintain a work-life balance with the effect that their participation in the workforce is reduced to only a few professions that suit their needs. This also reduces the substitutability of men and women for some jobs, increasing the intensity of the supply effect discussed earlier. Conclusively for Punjab, as an increasing influx of women in the workforce is choosing to lie in a very narrow spectrum of jobs, their excess supply adversely affects their wages.

The percentage contribution of each of the explained and unexplained gaps to the total wage gap is comparable to what other studies have estimated for Pakistan. For instance, Aslam (2009) estimates that the contribution of the unexplained gap to the total wage gap is 84%, while the remaining is explained by the explained gap, although she does so for the entire country. Similarly, Yasmin et al. (2021) estimate the contribution of the gender wage gap to be 90% or higher for all the years included in their analysis. Their analysis is too for the entire country. The estimate of the contribution of the unexplained gap to the total gender wage gap is 63% in the case of Ashraf et al. (1993), 86% in the case of Siddiqi et al. (1998), and 85% for Farooq and Sulaiman (2009). The results are also comparable to India, where this estimate is 75% of the total wage gap (Poddar & Mukpodhyay, 2019), and the United Kingdom, where the unexplained gap contributes

64% to the gender wage gap (Bernard, 2008). The estimates are, however, not comparable to developed countries such as the United States, where the unexplained gap contributes only 38% to the total wage gap (Blau & Kahn, 2017), or other countries such as Switzerland, where its contribution is only 8% (Strimmatter and Wunsch, 2021).

Estimation of Gender Gap at the Mean correcting for selection into paid employment and higher education using Heckman (1979) (Model 2a)

Table 2.7[11] presents our results for Model 2a, which corrects for selection into higher education along with selection into paid employment. Our exclusion restrictions for selection into paid employment are the same as in the previous section, and the exclusion restriction for selection into higher education is the 'average education of the household'. The values for years of education used in this model are the estimated values of years of education from a Heckman model explained previously in footnote 5. Panel An in Table 2.7, again like Table 2.6, gives the results from a base specification, and Panel B shows the results of the full specification. The first column for each year gives the coefficient estimated for each of the included variables, and the second column gives the percentage contribution of each of these variables to the total wage gap.

[11] The results for parental education used as exclusion restriction are available in the appendix A1. There is only a very small sample in both years for which parental education could be identified. The gender wage gap for this selected sample is very different from the whole sample. However, the direction of the change in percentage contribution of the explained and the unexplained gap is similar to what we find for the full sample.

Table 2. 7 Decomposition of the gender wage gap adjusted for selection into paid work and higher education (Model 2a)

Year	2006		2014	
	Contribution of Explanatory Variables to Gender Gap		Contribution of Explanatory Variables to Gender Gap	
Variable	**Coefficients**	**Percentage of Gap**	**Coefficients**	**Percentage of Gap**
Panel A: Base Specification				
Education	-0.029	-5%	0.013	2%
Experience	0.253	40%	0.14	20%
Married	-0.026	-4%	0.04	6%
Region	0.016	3%	0.022	3%
Explained Gap	0.214	34%	0.213	31%
Unexplained Gap	0.411	66%	0.485	69%
Total Wage Gap	0.625	100%	0.698	100%
Panel B: Full Specification				
Education	-0.03	-5%	0.003	0%
Experience	0.221	37%	0.147	21%
Married	-0.029	-5%	0.023	3%
Gender ratio: Professions	0.01	2%	-0.032	-5%
Gender ratio: Industry	-0.022	-4%	0.026	4%
Region	0.013	2%	0.019	3%
Industry	0.003	1%	0.003	0%
Profession	-0.012	-2%	-0.042	-6%
Explained Gap	0.156	26%	0.147	21%
Unexplained Gap	0.446	74%	0.544	79%
Total Wage Gap	0.601	100%	0.691	100%

Note: This table shows the decomposition of the gender wage gap into explained and unexplained parts correcting for selection bias using Oaxaca Blinder Methodology with Heckman two-step procedure for the years 2006 and 2014 using PSLM. The selection bias due to selection into paid work is corrected for using the household's possession of assets (Asadullah, 2019)) such as agricultural land, commercial building, poultry, livestock, residential building, animal transport, and the number of children below the age of seven in the household as the exclusion restrictions. The selection into higher education is corrected for using the 'average level of education of the household. The results of the selection function for each of these specifications are given in Appendix A2 (Tables

A22 & A23). The results with parental education as an exclusion restriction are given in Appendix A1.

From Table 2.7, we can see that when both the selection biases are corrected for the percentage contributions of the explained gap in the base specification increases by four percentage points and by nine percentage points in the year 2014. The unexplained gap consequently falls for both years. Additionally, the combined percentage contribution of the prime human capital determinants (education and experience) has increased from Model 1 to Model 2a in both the years and for both specifications. This could mean that the job opportunities that become available to people with higher education would penalize individuals for performing low on these two factors. When we did not account for the selection into higher education, we underestimated this penalty. However, when we compare the results of the base specification with the full specification, we see that the contribution of the prime human capital determinants falls, but it is still higher than what he had in the full specification in Model 1 for both years. The total explained gap falls on the other hand. This shows that although human capital determinants are important, other factors also play a role. When the supply effect is not controlled for, the impact of human capital determinants is overestimated. One could take this result to mean the following. First, the supply effect is an omitted variable in the base specification that, when not controlled for, overestimates the explained gap. Second, for this highly selective cohort with more than ten years of education, the human capital determinants matter relatively more. Third, for this selected group, the gender wage gap is affected much more by unexplainable factors than the explained gap, which could be because women are already catching up with men in terms of years of education and years of experience, thus shrinking the explained gap on the whole.

One result that is consistent both in Model 1 and Model 2a is the trends in the explained and unexplained gaps. The explained gap over years has fallen, and the increase in the total gender wage gap has mainly come from a rise in the unexplained gender wage gap both in the base and the full specification. In Model 2a, we are unable to demonstrate the supply effect. The explained gap falls as we control for it as opposed to in Model 1, where the explained gap increased. However, the supply effect, as the results also show, affects the gender wage gap both positively and negatively. The positive effect, as shown by coefficients on the industry variables in 2014 (4%), could be because the increase in the supply of women in limited jobs in a small number of sectors could be causing their wages to rise slowly compared to those of men, thus causing the gender wage gap to increase. The negative effect, on the other hand, mainly comes from the professional variables in 2014 (-11%). One way of interpreting this negative effect could be that the representation of women in a profession increases their bargaining power in those jobs, thus lowering the incidence of exploitation. Employers may also become increasingly aware of the performance of women and may get an opportunity to update their beliefs regarding the average productivity of women, thus lowering the incidence of gender inequality in labour market returns. As the negative effect is much higher than the positive effect, the ultimate effect for the supply effect is to cause the explained gap to fall, thus deviating from what we witnessed in Figures 2.4, 2.5, 2.6, and 2.7. Those figures reflect simple correlations between the supply effect and wages, but when other things are controlled for, the supply effect ends up going in women’s favor rather than hurting them.

Estimation of Gender Gap at the Mean correcting for selection into paid employment using Heckman and into higher education using IV

In Tables 2.8 (Model 2b) and 2.9 (Model 2c), we correct for selection into paid employment as we have been doing previously, and then to account for endogeneity bias in educational attainment, we instrument education attained with first the 'education level of the household head' (Model 2b) and the 'average education of the household' (Model 2c) as the instrumental variables[12]. Tables 2.8 and 2.9, like the previous tables, show the detailed wage decomposition for 2006 and 2014 first for the base specification and then the full specification. The first column in each year for each specification again gives the part of the explained gap due to that factor, and the second column gives the percentage contribution of each of these factors.

The results in both tables do not show any marked deviation from our results of Model 2a. First, in both of these models, our main result regarding the trend in the gender wage gap, which is increasing, remains evident. Second, the percentage contribution of the explained and unexplained gap and how they trend over time is also the same. The explained gap's percentage contribution is much smaller than that of the unexplained gap, and over the years, this percentage contribution drops further. The combined contribution of education and experience, however, is lower than that in Model 2a, although it is still higher than that in Model 1 for both specifications for both years in both Models (2b and 2c). What is also noteworthy about the impact of human capital determinants is that the contribution of education has been reduced to zero. The supply effect, as in Model 2a, also shows both negative and positive impacts. The contribution of industry variables in

[12] We also ran Model 2d that uses 'the number of female and male individuals in the households' but do not include the results of this model in our main text as the first stage with this IV was not significant. The results for this IV are available in the appendix B1 Table B11.

Model 2b in 2014 is still four percent, and it rises slightly to five percent in Model 2c. On the other hand, the 'profession' variables' contribution to the explained gap is negative ten percent in Model 2b and drops further to negative thirteen percent in Model 2c. Regardless of the magnitude, the main results regarding the supply effect continue to hold. The negative effect overpowers the positive effect, thus causing the explained gap to fall. Thus, correcting for endogeneity bias has the same qualitative effect on our results as correcting for selection bias; however, the quantitative results differ slightly.

Table 2. 8 Decomposition of gender wage gap adjusted for selection and endogeneity bias (IV: Average education level of the household)

Year	**2006**		**2014**	
	Contribution of Explanatory Variables to Gender Gap		Contribution of Explanatory Variables to Gender Gap	
Variable	**Coefficients**	**Percentage of Gap**	**Coefficients**	**Percentage of Gap**
Panel A: Base Specification				
Education	0	0%	0	0%
Experience	0.107	19%	0.152	25%
Married	0.046	8%	0.017	3%
Region	0.037	7%	0.017	3%
Explained Gap	0.189	34%	0.186	30%
Unexplained Gap	0.369	66%	0.428	70%
Total Wage Gap	0.559	100%	0.614	100%
Panel B: Full Specification				
Education	0	0%	0	0%
Experience	0.098	18%	0.134	22%
Married	0.033	6%	0.017	3%
Gender ratio: Professions	0.012	2%	-0.031	-5%
Gender ratio: Industry	-0.024	-5%	0.027	4%
Region	0.028	5%	0.016	3%
Industry	0.003	1%	0.002	0%
Profession	-0.02	-3%	-0.046	-8%

Explained Gap	0.13	24%	0.12	20%
Unexplained Gap	0.406	76%	0.488	80%
Total Wage Gap	0.536	100%	0.608	100%

Note: This table shows the decomposition of the gender wage gap into explained and unexplained parts correcting for selection bias using Oaxaca Blinder Methodology with Heckman's two-step procedure for the years 2006 and 2014 using PSLM. The selection bias due to selection into paid work is corrected for using the household's possession of assets (Asadullah, 2019)) such as agricultural land, commercial building, poultry, livestock, residential building, animal transport, and the number of children below the age of seven in the household as the exclusion restrictions. The endogeneity due to sample selection and omitted variables is corrected for using the average education level of the household excluding individual 'i' as IV. The results for the first stage of IV regressions of all specifications are available in Appendix B1 Table B12.

Table 2. 9 Decomposition of the gender wage gap adjusted for selection and endogeneity bias (IV: Education level of the household head)

Year	**2006**		**2014**	
	Contribution of Explanatory Variables to Gender Gap		Contribution of Explanatory Variables to Gender Gap	
Variable	**Coefficients**	**Percentage of Gap**	**Coefficients**	**Percentage of Gap**
Panel A: Base Specification				
Education	0.000	0%	0.000	0%
Experience	0.117	19%	0.178	25%
Married	0.052	8%	0.020	3%
Region	0.044	7%	0.020	3%
Explained Gap	0.213	34%	0.218	31%
Unexplained Gap	0.412	66%	0.485	69%
Total Wage Gap	0.626	100%	0.703	100%
Panel B: Full Specification				
Education	0.000	0%	0.000	0%
Experience	0.108	18%	0.156	22%
Married	0.037	6%	0.020	3%
Gender ratio: Professions	0.012	2%	-0.029	-4%
Gender ratio: Industry	-0.018	-3%	0.025	4%
Region	0.031	5%	0.019	3%

Industry	-0.002	0%	0.006	1%
Profession	-0.015	-2%	-0.044	-6%
Explained Gap	0.154	26%	0.153	22%
Unexplained Gap	0.445	74%	0.548	78%
Total Wage Gap	0.599	100%	0.701	100%

Note: This table shows the decomposition of the gender wage gap into explained and unexplained parts correcting for selection bias using Oaxaca Blinder Methodology with Heckman's two-step procedure for the years 2006 and 2014 using PSLM. The selection bias due to selection into paid work is corrected for using the household's possession of assets (Asadullah, 2019)) such as agricultural land, commercial building, poultry, livestock, residential building, animal transport, and the number of children below the age of seven in the household as the exclusion restrictions. The endogeneity due to sample selection and omitted variables is corrected for using the education level of the household head as IV. The results for the first stage of IV regressions of all specifications are available in Appendix B1.

As we find all of these results to hold for all our chosen instruments, one may take it to mean that the broad conclusions derived from the analysis regarding the relative sizes and contributions and the trends of the explained and unexplained gaps are valid. However, the results regarding the relative sizes of individual coefficients may be interpreted with caution, as all the instruments used are trying to proxy for the actual instruments used in the literature already and may not be the best choices for instruments. For instance, the education of the household head is a proxy for parental education, and similarly, the average education of the household and gender composition of the household proxy for the gender composition of siblings. Due to limitations of our data, we are unable to use the actual instruments and therefore would interpret these results with caution. Regardless of the choice of instrument or estimation technique, one consistent result is the sizes of explained and unexplained gaps and the trend in those.

Additionally, one thing that we cannot conclusively say about these results is in what direction the supply effect affects the gender wage gap. With selection correction, a movement from the base to the full specification increased the explained gap and decreased the unexplained gap. Here, with the IV estimations coupled with selection correction, the explained gap falls, and this fall mainly originates from the supply effect. There is, however, a slight hint of a within-sector/occupation gender wage gap, as shown by a positive coefficient of the gender ratio in professions in 2006 and a positive coefficient on the gender ratio in the industry in 2014. However, these results need to be interpreted with caution, as our instruments are not perfect. Second, another important consideration to keep in mind is that the professions and industries are currently defined at the one-digit level to stay consistent between years. However, if the classification of these is taken to finer and more minute levels, one may be able to see the supply effect more prominently. Currently, it is possible that due to this broader classification, the supply effect is being averaged out and is not too strong.

Estimation of Gender Gap Across the Wage Distribution

To study the trend in the gender wage gap across the wage distribution, table 2.10 presents the results for the wage decomposition analysis at the top, middle, and bottom of the wage distribution. While overall from table 2.2 we saw that the gender wage gap has increased, to analyse the extent to which workers at different parts of the wage distribution have been affected by the wage disparity we see that workers at the bottom of the wage distribution have been hurt the most as only for the bottom twenty-five percent do we see the total wage gap rising both in the base and the full specification (Tabe 2.10, panel C). For the middle and the top of the wage distribution, the total wage gap over years has fallen both in the case of base and the full specification. Another important point to note is that the gender wage gap is highest at the bottom of the wage distribution, followed by the top twenty-five percent, and finally, in the middle, it is the lowest. This is true for both the base and the full specification and across the years (Panel C). Therefore, the first finding from the wage decomposition analysis across the wage distribution is that the gender wage gap is highest at the bottom of the wage distribution, and it has further increased over the years while it has fallen for the rest of the distribution.

Table 2. 10 Decomposition of Gender Wage Gap Across the Wage Distribution: 2006 & 2014

Year	2006		2014	
Variable	Base Specification	Full Specification	Base Specification	Full Specification
Panel A: Explained Gap				
Bottom 25%	-0.052	-0.06	0.12	0.136
Fiftieth Percentile	0.023	-0.026	0.006	-0.001
Top 25%	0.008	0.076	0.012	0.056
Panel B: Unexplained Gap				
Bottom 25%	0.264	0.295	0.146	0.139
Fiftieth Percentile	0.044	0.081	0.014	0.019
Top 25%	0.118	0.056	0.082	0.043
Panel C: Total Wage Gap				
Bottom 25%	0.211	0.236	0.266	0.275
Fiftieth Percentile	0.067	0.055	0.019	0.018
Top 25%	0.126	0.132	0.095	0.099

Note: This table shows the decomposition of the gender wage gap into explained and unexplained sources using Oaxaca Blinder Methodology for the years 2006 and 2014 using PSLM at different points of the wage distribution. The base specification includes human capital determinants, i.e., education and experience, and regional dummies, and the full specification additionally controls for industries, professions, and the gender ratio in industries and professions.

The other important results are regarding how the gender wage gap splits between the explained and the unexplained part. At the base of the distribution in the base specification in 2006, the explained wage gap (Panel A, Table 2.10) is the lowest, whereas as we move up the wage distribution, the explained wage gap increases up to the middle and then begins to decline. Almost a decade later, the situation is the opposite, as the explained gap at the bottom of the wage distribution in the base specification in 2014

(Column 3, panel A Table 2.10) is the highest and falls subsequently as we move up the wage distribution. In the full specification in 2006, when we control for the industry and occupation-specific gender, the explained gap increases only at the top of the distribution while falling for the rest. This shows that when we did not control for the supply effect, the explained gap was underestimated at the top. In 2014, as one can see from column 4 of Panel A of Table 2.10, things have not changed much, as the explained gap is still highest at the bottom of the wage distribution and lowest at the middle. One can explain this high explained gender gap at the bottom of the wage distribution by the difference in the observable characteristics. At the bottom of the wage distribution, as shown in Table 2.11, there is a significant difference in both education levels and years of experience attained by men and women. Men seem to be doing much better on these observable characteristics, but as one moves to the top of the distribution, the years of experience differential between men and women seems to be shrinking and even seems to be getting better than men with respect to education. This gender gap in observable characteristics at the bottom could reflect stricter adherence to gender norms that are more prevalent in this class of society. Therefore, the gap in years of experience could reflect women's career choices to suit their gender roles, which, for instance, demand irregular or shorter work lives, negatively affecting their work experience. Similarly, the gap in years of education could reflect the families' preference to invest in the human capital of men rather than women.

Table 2. 11 Prime Human Capital Determinants Across the Wage Distribution: 2006 & 2014 (PSLM)

	Year: 2006			Year: 2014		
	(1)	(2)	(3)	(4)	(5)	(6)
Variable	Female	Male	Difference	Female	Male	Difference
Panel A: Bottom 25%						
Years of Experience	6.726	12.099	5.373***	7.586	11.076	3.490***
	(4.857)	(11.528)		(5.617)	(10.224)	
Years of Education	13.28	13.481	0.201	13.699	13.045	-0.654***
	(1.307)	(1.441)	(0.268)	(1.539)	(1.661)	
Panel A: Top 25%						
Years of Experience	16.131	20.469	4.338***	19.276	21.774	2.497***
	(9.164)	(10.545)		(10.231)	(10.168)	
Years of Education	14.604	14.14	-0.464***	14.605	14.072	-0.534***
	(1.547)	(1.566)		(1.713)	(1.754)	

Note: This table shows the mean years of experience and the mean years of education attained by men and women in the top and bottom 25% of the wage distribution for the years 2006 and 2014 using PSLM for the respective years.

Finally, the unexplained portion of the gender wage gap is the highest at the bottom of the wage distribution, falling subsequently for the rest of the distribution in both years, making gender discrimination a more serious concern at the bottom than at the top. At the top of the distribution in both years, the unexplained gap matters almost as much for the gender wage gap as does the explained gap. There is a drop in the unexplained gap's magnitude from 2006 to 2014 at the top. This could reflect more progressive values or the greater acceptability of households to women going out of the house and participating in the workforce. For instance, PCSW (2018) shows that the incidence of early marriages of girls and early childbearing falls with a rise in household socioeconomic status and women's education level. From the demand side of the labour market, this could also be reflective of workplaces becoming more accommodative and cognizant of women's expected gender roles and therefore creating space and opportunities to facilitate them. For instance, Delcuvellerie et al. (2019), using evidence from Lahore and Punjab, show that larger firms that can bear a relatively greater burden of integration costs tend to employ more women than smaller firms.

What is also noteworthy is that the explained gap after the inclusion of the gender ratios in the full specification only increases for the top ten percent. Similarly, the unexplained part also falls for the top ten percent in the full specification for both years. This shows that the supply effect is only prevalent at the top of the distribution. For the rest of the distribution, other factors seem to be at play and could be a potential area for future research.

Other Possible Explanations of Gender Wage Gap

The gender gap in labour market returns is attributed to the observable differences between men and women, such as education attained or experience gained, but their relative importance in explaining the gender wage gap is small compared to the very large contribution of the unexplained differences. Additionally, these factors themselves are affected by the ingrained biases of society. These biases or social barriers ultimately affect labour market returns either directly or indirectly through these explained differences. Here, in this section, we attempt to unpack some of the possible explanations for the gender wage gap, especially in the context of Pakistani society, which may affect women's ability to even take part in any productive work.

2.1 Household allocation of resources to education: The gendered perspective

If households view expenditure on the education of children as an investment, then they may invest in building the human capital of an individual whose prospects of doing better in the labour market are higher. In the context of Pakistan, this would imply that households typically invest more in the education of sons than daughters as they view them as old-age support and that men tend to fare better in the labour market, so it makes sense for them to invest where the returns are higher.

Aslam and Kingdon (2002), using the Pakistan Integrated Household survey, show evidence of a pro-male bias in the decision regarding sending children to primary school, but once enrolled, there is a pro-female bias in the education expenditure of younger cohorts (5-9 yrs.). For older children above the age of nine, there is a pro-male bias both in the decisions regarding enrolling and subsequent education expenditures. They explain their results in light of parents' investment motive, for whom sons are providers of old-age support, and that labour market returns are higher for men versus women. So for them, it pays off more to invest in the education of boys than that of girls.

We also show in Table 2.12 how the expenditure on education of children differs significantly for a male child vs a female child. To carry out this comparison, we made use of two rounds of the Household Integrated Expenditure Survey (HIES) for the years 2005 and 2015 for Punjab. We show that households tend to spend significantly more on fee and other education-related expenditures, such as on uniforms, books, school supplies, private tuition & transport, for boys than for girls, and this difference has increased over time.

Table 2. 12 Difference in means of education expenditure by gender

	2005			**2013**		
	Male	Female	Difference	Male	Female	Difference
Fee†	590.07	398.46	191.61***	1879.56	1335.29	544.27***
Other expenses‡	466.85	349.22	117.64***	1778.64	1467.28	311.36***

Source: Household integrated survey 2005 and 2013. †This head includes expenditures on admissions, registration fees, funds, donations, and exam fees. ‡ This head includes expenditure done on the uniform, books, school supplies, private tuition & transport. This table reports expenditures made by the households on different educational needs of children in the years 2005 and 2013. The difference column shows the difference of means of each head and reports if this difference is significant or not.

We also show estimates of the Engle curve methodology, which is a regression of the share of a household's budget allocated to education on the proportion of male and female children in various age brackets. Our results for the Engel curve methodology are presented in Figure 2.8. I show that for age brackets 5-9, 10-14, and 15-19, there is a significantly higher proportion of budget allocated to education if there is a higher proportion of males in the household in these age brackets compared to females (Table 2.13). However, in 2014, the trend seems to be changing, as for the 5-9 years age bracket, there is still greater expenditure on education by a household if there is a relatively greater proportion of boys in this age bracket compared to females, but for 10-14 years, there is no significant difference between what households choose to spend on the education of boys vs. girls, and for the age bracket of 15-19 years, households tend to spend significantly more on education if there is a higher proportion of girls in the household compared to boys in this age bracket.

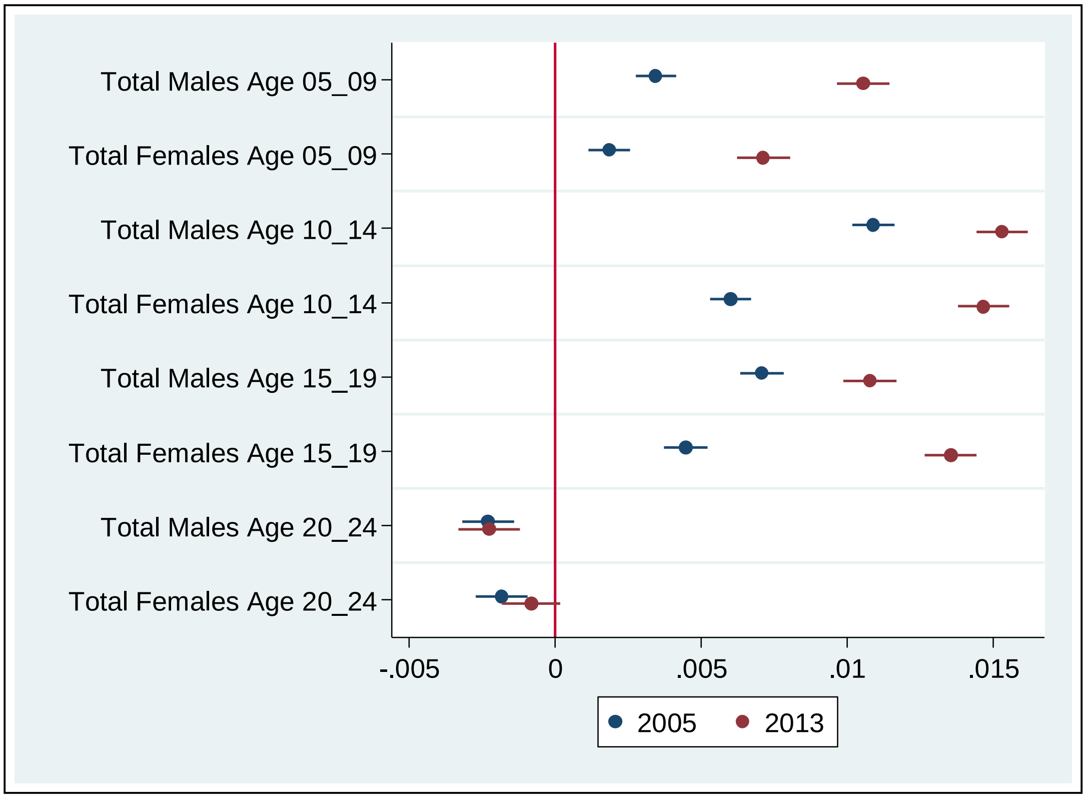


Figure 2. 8 Coefficient plots of the Engel curve methodology (HIES, 2005 and 2015)

Note: This figure shows coefficient plots of the regression of the log of budget share of education expenditure in the household's total expenditure on the sum of total male and female members in a household in age brackets of 5-9, 10-14, 15-19 and 20-24 years in 2005 and 2013. This is a household-level regression.

Table 2. 13 T test of difference in estimated coefficients from the Engel curve

	2005			2013		
Age Group	Male Coeff	Female Coeff	F-stat of Difference in the coefficients of male and females	Male Coeff	Female Coeff	F-stat of Difference in the coefficients of male and females
05-09	0.0034	0.0018	12.79	0.0034	0.0018	33.89
10-14	0.0109	0.006	98.38	0.0109	0.006	1.1
15-19	0.007	0.0044	24.39	0.007	0.0044	18.9
20-24	-0.0022	-0.0018	0.52	-0.0022	-0.0018	3.81

Note: This table shows the statistical significance of the difference in the coefficient estimates of the gender-specific count of household members in different age brackets. H_0 for the test is for the coefficient estimates of males and females to be equal and therefore their difference to be zero. An F value greater than 3.95 means that H_0 can be rejected, and thus, it can be safely concluded that coefficient estimates on male and female variables are significantly different from each other.

We also use a hurdle model to see if there is any difference in how households allocate resources to the education of boys versus girls. The first step of the hurdle model is a regression of a binary indicator for ‘any expenditure done on an individual’ on the gender of this individual. The second stage is a regression of ‘actual education expenditure’ done on this individual on their gender. This second stage is run for a subset of individuals on whom there was some nonzero or positive expenditure incurred by the household. In this model, we also see in Figure 2.9 that in 2005, there is a significantly higher probability of households incurring some nonzero expenditure on the education of a child if it is a male and that conditional on there being a positive education expenditure, there is a significantly higher expenditure on the education of a male child compared to a female child. In 2015, we obtain the same results for stage 2, but for stage one, there is no significant difference in the probability of a household spending anything on the education of a male or a female child.

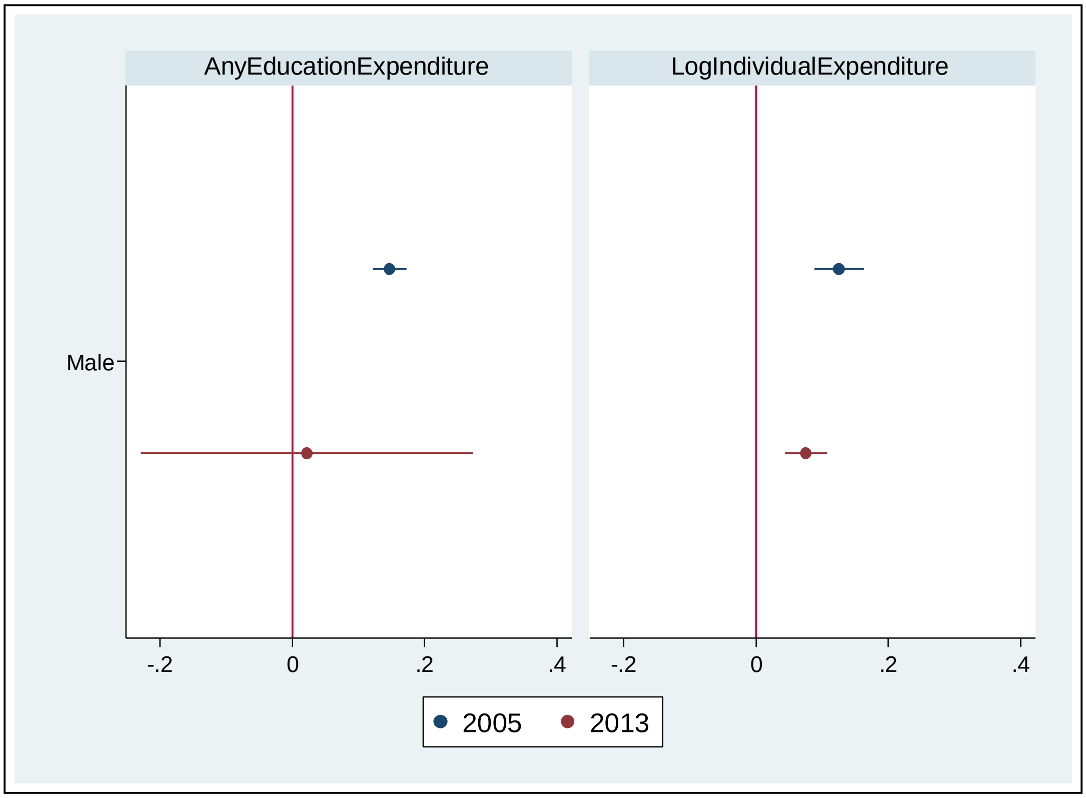


Figure 2. 9 Coefficient plots of the Hurdle model (HIES, 2005 and 2015)

Note: This figure shows the coefficient plots of the two stages of a hurdle model. The panel on the left is the first stage, which is an individual-level regression of 'Any education expenditure' (an indicator variable equal to 1 if the household incurred any expenditure on the education of this individual) on a dummy variable for gender (Male equals 1 for males and 0 for females). The panel on the right is a regression of the 'Log of individual-specific education expenditure' on the male dummy. This regression is run for only those individuals on whom some positive education expenditure was incurred by the household. Both panels represent individual-level regressions.

Therefore, from both the Engel curve and the hurdle model, we find a substantial pro-male bias in regard to allocating resources for the education of a child, especially at the primary level. This finding points to how households treat children differently depending on their gender in regard to investing in their human capital; however, over the study period, there is evidence that households tend to treat males and females going to postsecondary classes either equally or that there is even a pro-female bias, as shown by the coefficient sizes of the 15-19 age bracket in Figure 2.8. Additionally, in figure 2.9 in

2014 one does not see any significant difference in the probability of household spending anything on the education of an individual depending on their gender. These two results may partly explain the negative explained gap due to education in our wage decomposition analysis for individuals with tertiary education. The low returns for women in the labour market may be taken as signals by the households who would choose to invest in the human capital accumulation of a child whose prospects of earning higher are brighter. This may lead to a mutually reinforcing cycle of gender wage gaps and differential treatment of the households based on gender (Averkamp, 2020). This phenomenon is particularly strong in the initial years of education when the households have to decide whether to send a child to school or not, but once they are enrolled and progress to higher levels of education, households tend to subsequently discriminate less.

Mobility

The LEAPS[13] survey shows that even though parents consider girls' schooling as a means to improve their social and financial standing, there is a persistent gender gap in primary enrollment. Exploring this puzzle further, research shows that anything distance to school stands as the most crucial determinant of girls' enrollment. When a school is next door, there is no gender gap in enrollment, but enrollment begins to increase sharply for those who live more than 100 meters away. Similarly, in another study by Asim Khwaja and coauthors, they show that take-up rates for a vocational training program are fifty percent higher when the training center is located within the village (Cheema et al, 2019). Similarly, Field et al. (2020) highlight how the mobility of women in Pakistan is

[13] Mohydin, R. & McIntyre, V. (2018, Jan' 30). The Puzzle of Female Enrollment in Pakistan. RISE. https://riseprogramme.org/blog/puzzle_of_female_enrollment_in_pakistan

severely restricted. Distance seems to matter because of other considerations, such as conservative values, the monetary cost of travel, and other safety concerns.

Delcuvellerie (2019) shows that among the 'currently not working' women, only 20% expressed interest in working, and 36% of these women had acquired more than twelve years of education. They also show that firms in the Lahore area also showed a willingness to hire women, and it is higher for firms where there are already women working. This finding is presented by the authors as a paradox that women are willing to work and firms are willing to hire then why is the female labour force representation so low in their sample? Through further exploratory work, they find mobility to be the most important constraint, as firms of various sizes in their survey indicated that they took into account applicants' place of residence and the mode of transport they would use to commute. Similarly, 90% of women in their survey said that they would be more willing to work if safe transport were available.

The Family Economics Perspective

Averkamp (2020) argues that women may also face lower returns in the labour market, as families tend to prioritize the careers of individuals who have higher earning potential. For instance, households may choose to migrate in search of better job opportunities for the individual having better earning potential, thereby increasing the probability of hurting women's career prospects. The unexplained gender wage gap may also take into account some of this effect. Indeed, the Labour Force Survey for 2014 shows that even for a very selected sample of men and women with higher education who are between the ages of 15 and 65, the percentage of female labour force participants who have migrated either due to marriage or with the spouse within or to another province is

63.3%, compared to only 1.58% for men. Most men (46.5%), on the other hand, have migrated either due to a job transfer, in search of a job, for a new job, or business. The proportion of women in these categories is only 6.92%. Table 2.14 also gives some additional indicators to highlight some additional social barriers to labour force entry that women have to face to fulfil their expected gender role. Due to all of these social barriers, women end up either staying out of the labour force or in jobs that pay less. Over the study period, these indicators do not seem to have improved much for women to say that the social barriers that mattered for women ten years ago matter less or no more in 2014.

Table 2. 14 Other social barriers affecting labour market outcomes of women (LFS: 2006 and 2014)

Indicator	**2006**	**2014**
Percentage of women who migrated due to marriage or with a spouse	66.39%	63.30%
Percentage of men who migrated due to marriage or with a spouse	2%	1.58%
Percentage of women who migrated due to job	6.72%	6.92%
Percentage of men who migrated due to job	61.60%	46.50%
Average weekly hours worked by women	36.83	38.47
Average weekly hours worked by men	48.31	46.62
Family responsibilities as the main reason for leaving the last job (women %)	25%	23%
Family responsibilities as the main reason for leaving the last job (men %)	6.67%	5%
Not available to work during the last week due to housekeeping (women %)	78.19%	76%
Not available to work during the last week due to housekeeping (men %)	2.62%	0.98%
Not available to work during the last week due to studies (women %)	19.63%	21%
Not available to work during the last week due to studies (men %)	51.53%	71%

Note: This table is constructed using two rounds of the Labour Force Survey for the years 2006 and 2014. Each cell represents a percentage of individuals.

Social Norms

Social norms that define gender roles and shape expectations regarding individuals' behavior and their subsequent actions are another important barrier to women's access to opportunities in Pakistan. For instance, according to a recent survey by the Punjab Commission for the status of women (2018), family permission (26.1%), distance (22.3%), domestic responsibility (27.5%), or lack of financial means (33.2%) are the most cited reasons by women in Punjab for never having attended any formal education or training. Similarly, lack of qualification (50%), family permission (34.4%), domestic responsibilities (41.4%), and transport (34%) are also the most cited supply-side barriers for women to work according to the same survey.

The social norms that define gender roles also restrict job opportunities for women, e.g., the most cited demand-side barriers by women in the PCSW survey are lack of flexibility (24.3%), lack of appropriate job opportunities (41%), male colleagues (34.6%) and inadequate training opportunities (36.96%). Finding a job that addresses all of the above-stated factors often leads to women facing a trade-off between avoiding these factors and higher returns.

Early marriages also impede women's access to opportunities and affect their subsequent labour market outcomes. PCSW (2018) shows that approximately 15% of women aged between 20-24 years in their sample got married before they were eighteen years of age, and this incidence of early marriages seems to fall with the level of education and level of wealth. Similarly, early childbearing and the subsequent burden of domestic responsibilities at a very early stage in life also hinder women's human capital accumulation. PCSW (2018) shows that for women aged 20-24 years, approximately 14% had their first child before the age of eighteen. However, like early marriages, early childbearing also falls with the level of education and wealth.

Overall, in this section, we have tried to highlight some of the social barriers that women have to face at every stage in their life that ultimately affect their labour outcomes by making them or their households face decisions that often involve a trade-off between higher returns or fulfilling their expected gender roles or abiding by social norms.

Discussion

The analysis of Punjab's labour market shows that the gender wage gap has been on the rise despite there being an improvement in their human capital. Women seem to have improved, especially in terms of postsecondary educational attainment, where we show in figure 2 that the gender gap in enrolment rates at the postsecondary level has been falling over time. However, women still lag behind men in terms of years of experience; however, the gap between men and women has also started to narrow, and this is especially true at the top of the wage distribution (Table 12). Another important observation from our data is that while women mostly enter paid employment, many of them tend to enter a limited set of jobs in very selected sectors (Tables 3 and 4). This selective nature of labour force participation of highly educated women seems to have some correlation with how their wages trend over time (figures 4 and 5). We intended to find the plausible causes of the increasing gender wage gap in Punjab and understand how much of it is being contributed to by the standard human capital determinants and if the supply effect has some implications for the gender wage gap. Simply put, we hypothesized that women over years have populated only a few sectors and occupations and that their oversupply in these jobs may have limited the growth of their wages in comparison to those of men in these sectors. Moreover, since there is limited substitutability between genders for many jobs, the supply effect becomes an even larger concern. Limited substitutability arises because of women's higher preferences for certain job attributes, such as flexible timing, a safe work environment, the distance of the job from home, and child-friendly jobs.

We employed the Oaxaca Blinder Methodology to understand the causes of the gender wage gap, but one methodological concern with this analysis is our highly selected sample. The selection concerns in our sample arise from two sources. First, due to selection into paid work and second, due to selection into higher education. In our analysis, therefore, we rely on Heckman (1979) and IV methodology using multiple exclusion restrictions and instrumental variables to correct for selection bias and endogeneity bias. We present our results for all our choices of exclusion restrictions and IVs to compare our results across models and be able to say something conclusively regarding the gender wage gap and its contributors. For ease of exposition, we also present our results from different models together in Table 2.15.

We show that the gender gap is substantial for both the years included in the analysis and that it shows no sign of improvement or convergence of men's and women's wages, it has increased over the years. Second, the analysis of the gender wage gap across the entire distribution shows that the total wage gap falls as you move up the wage distribution where the coefficients effect or the gender discrimination is more to be blamed for the gender wage gap than the endowments or the explained effect. Third, the gender discrimination/coefficients effect falls as you move up the wage distribution, whereas the endowments become more important for determining returns as one moves up the wage distribution.

Additionally, to test the supply effect to see if the supply of labour matters for the gender wage gap, we re-estimate the gender wage gap after controlling for the ratio of men and women in an industry and occupation. Our main results, as discussed above, remain consistent when we only account for selection into paid employment. Additionally, the unexplained part of the gender wage gap falls for both years, while the explained part increases once the industry and occupation-specific ratios are controlled for, thus pointing to the fact that by controlling for the relative supply of men and women in an industry or occupation, we can explain some part of the previously unexplained gender wage gap.

However, when we attempt to control for selection into higher education and endogeneity bias, the unexplained gap increases, and the explained gap falls. We interpret the fall in the explained gap after controlling for both types of selection biases as pointing to the fact that one is dealing with a highly selected sample. For this cohort, the observed characteristics that we controlled for seem to matter less for the gender wage gap. This could be an outcome of two opposing effects of the increased female labour supply. One factor positively affects the gender wage gap by making wages grow slowly if many women are competing for a limited number of jobs. The second one affects the gender wage gap negatively because of an increased representation of women in the labour force having a favorable impact on their bargaining power and negotiation opportunities, and the employers get a chance to update their beliefs regarding the average productivity of women.

On the other hand, the unexplained gap increases further as the supply effect is controlled for in models where both selection biases are also accounted for. These results show that the gender wage gap in this sample is not so much because of allocative discrimination as it is because of valuative discrimination (Petersen and Morgan, 1995). Women of this cohort face a disadvantage in the labour market not because they have completely different skills or are going to completely different jobs compared to men. They suffer despite going to occupations that men also enter and therefore have skills and talent that are at par with men. Initially, we hypothesized that the oversupply of women in limited jobs may be lowering their wages, but our empirical analysis shows that the increase in the gender wage gap in Punjab over years is more a case of valuative discrimination where women's work is undervalued compared to that of men. The premium men enjoy is largely because of the difference in which the labour market treats men and women with similar characteristics differently. This differential treatment has a deeper explanation for it and may stem from other underlying social barriers, such as mobility, social norms, allocation of education expenditure by household by gender, family economics perspective, and many others.

Table 2. 15 Comparison of coefficients across different models:

Year	Base specification				Full specification		
	Model	Total wage gap	Explained gap	Unexplained gap	Total wage gap	Explained gap	Unexplained gap
2006	Model 1	0.625	0.179	0.446	0.602	0.185	0.417
			(29%)	(71%)		(31%)	(69%)
	Model 2a	0.625	0.214	0.411	0.601	0.156	0.446
			(34%)	(66%)		(26%)	(74%)
	Model 2b	0.559	0.189	0.369	0.536	0.13	0.406
			(34%)	(66%)		(24%)	(76%)
	Model 2c	0.626	0.213	0.412	0.614	0.186	0.428
			(34%)	(66%)		(30%)	(70%)
2014	Model 1	0.689	0.15	0.538	0.69	0.186	0.504
			(22%)	(78%)		(27%)	(73%)
	Model 2a	0.698	0.213	0.485	0.691	0.147	0.544
			(31%)	(69%)		(21%)	(79%)
	Model 2b	0.614	0.186	0.428	0.608	0.12	0.488
			(30%)	(70%)		(20%)	(80%)
	Model 2c	0.703	0.218	0.485	0.701	0.548	0.153
			(31%)	(69%)		(22%)	(78%)

Note: Each cell in this table represents the estimates of gaps from the respective tables in which the results of each model are given. The values in the parentheses are the percentage contribution of each of the gaps in the total gap for that model for that year.

Conclusion

This particular study is about understanding the trend in the gender wage gap in Punjab for over a decade and understanding its potential sources by breaking it down into explained and unexplained sources using the Oaxaca Blinder Methodology. The motivation for this work comes from the two conflicting statistics in the labour market. One that shows that women are catching up with men in terms of human capital determinants and the years of experience (although there is still a long way to go before the experience gap is bridged, at least this gap has fallen). The other shows that over the years, the gender wage gap has increased. These findings present themselves as a paradox that despite improvement in human capital, women continue to suffer in the labour market. We hypothesize that this conflicting result could be due to the selective nature of the participation of women in a very limited set of sectors and occupations causing their wages to rise slowly when many women compete for very few jobs.

We execute our analysis on individuals who are in paid work and have acquired more than ten years of education. This makes our sample highly selective, as very few people enter into paid employment, and for a country such as Pakistan where the literacy rates are very low, getting into higher education (especially for women) is not a norm. We correct for both sources of selection bias in our analysis using Heckamn (1979) and IV methodology. Our results show that the gender wage gap is contributed much more by the unexplained sources and less by the explained sources. Over the years, the increase in the gender wage gap originates mainly from an increase in the unexplained gender wage gap.

When we control for the supply effect to determine how much the selective nature of the participation of women in the labour force is costing their wages, we find evidence of both a positive and a negative effect. We feel this result needs to be probed further in future research. This finding that more than 90% of women are found in a very selected number of jobs is itself very important. We need to understand how this affects the labour market outcomes of women by using other methods and techniques as well. This is important, as lessons learned from such an analysis can be used to reduce the incidence of gender inequality in labour market outcomes.

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3. Paper II: Unequal Pay for Equal Education! A Case of Gender Wage Gap from Punjab, Pakistan

Introduction

The gender gaps in primary and lower secondary enrolment in Punjab are smaller than those in other provinces, but boys still outnumber girls at both levels. At the higher secondary (intermediate) level, the gender gap shrinks, and at the BA/BS/postgraduate level, girls outnumber boys (PSLM, 2014). In this paper, we propose to look at the pays-off in the labour market to increase higher educational attainment and the extent to which these returns differ for men and women to see whether these differences can to some extent explain the reversal in the gender gaps in education/enrollment. The returns to any level of education broadly fall into three categories: i) private financial returns, ii) private nonfinancial returns such as the availability of better jobs and better working conditions, and iii) social returns. In this paper, however, we focus only on private financial returns by examining the effect of higher education attainment on wages and the gender gap in these returns.

To estimate a causal link between the returns to tertiary education in Punjab and the gender gap in these returns, we make use of the instrumental variable technique. Making use of the exogenous variation in the supply of higher education institutes, this paper uses the 'total number of available tertiary educational institutes at the district level in Punjab' as an instrument. The steady increase in tertiary education institutes reflects improved access to tertiary education for boys and girls for two reasons. First, the expansion of tertiary education facilities ‘exogenously’ decreases the costs associated with attaining more education. It does so by making access to college education cheaper for individuals when a new college is constructed in the local area. Second, having a college in one’s area may also reduce mobility concerns, which are an important hurdle, especially for women in the way of attaining education (Cheema et al., 2019). In addition to using an IV, we also make use of the region and time fixed effects in our first stage to control for region-specific and time-varying unobserved factors that may cause omitted variable bias if not accounted for.

The first stage of this analysis is a regression of educational attainment on the number of tertiary education institutes available in a district. In estimating the first stage, our two identifying assumptions are a) the relationship between changes in college availability and changes in educational attainment is not reflective of changes in development in general and b) the exact timing of college opening in a given district is not driven by demand for education.

To show that the changes in college availability and changes in educational attainment are related regardless of the level of development, we show that first-stage results are robust to controlling for the development of a region using various community-level indicators of development. Additionally, the responsiveness of years of education to variation in the supply of tertiary educational institutes is evident only for the relevant age cohorts, i.e., from 16 to 32 years. The results of the first stage are null for sample observations that lie just above and just below the relevant age cohort. This again is to show that the first stage results are not reflective of development in general because if they were there should be a significant positive relationship between the two regardless of the age brackets because of the confounding effect of regional development.

The main findings of this analysis are that there is a positive significant relationship between estimated years of education from the first stage and income levels. Another important result is that men on average earn significantly more than women regardless of the level of education; however, an extra year of education brings higher returns to women than to men. This implies that the gender earnings gap tends to fall as we increase the education distribution. Whatever the reason for the differential in the earnings of men and women, discrimination or difference in their respective productivities, the results show that as the years of education attained increase, the earnings differential between men and women narrows down.

The first-stage results show that greater availability of colleges at the district level is significantly associated with higher educational attainment at the individual level. Moreover, the impact of an increased supply of tertiary education institutions on tertiary education attainment is higher in low Human Development Index (HDI) districts than in the high HDI districts of Punjab. This is an important result from a policy perspective, as it shows that investing in the physical infrastructure in less developed regions yields the greatest returns.

This work is a contribution to the study of labour markets in Pakistan, as tertiary education is still an understudied area in Pakistan. To that end, the analysis makes a significant contribution to the literature on tertiary education by introducing a unique instrument, the district-level supply of education, i.e., Number of Arts and Science Intermediate, Degree, and PostGraduate Colleges for Boys and Girls in a given district at a given point in time in Punjab. A related contribution of this study is that a pooled cross-section with a very large number of observations has not been used to study the dynamics of returns to tertiary education in Pakistan. This has been achieved by making use of five rounds (2006, 2008, 2010, 2012, and 2014) of the household level survey, Pakistan Social and Living Standards Measurement (PSLM), covering a decade. This gives us a very large number of observations, i.e., approximately 10,000 in this case, and sufficient data points to study this research question.

Our analysis derives its significance from the important lessons it bears for policy. For instance, the returns to tertiary education as projected over the life cycle reflect the expectations that influence current student decisions to participate in higher education. If the returns increase with years of education, then there is a positive signal from the labour market, and it should effectively lead to greater investment in human capital accumulation. The literature has previously shown that households respond to information regarding returns to education (Jensen, 2012; Attanasio and Kaufmann, 2009). The results regarding the gender gap in returns to tertiary education can be taken as confirmation of this hypothesis, as higher marginal returns could be a reason why girls' enrollment has been increasing in tertiary education over the past decade (Table 3.1).

The first stage of this analysis also has at least two very important policy implications. First, the results show the importance of investing in physical capital for the accumulation of human capital. A concerted effort to plan the expansion of the supply of education, especially in areas where there is a dearth of tertiary educational institutes, may allow for the possibility of accumulating greater years of education for individuals who are at the margin. Second, the increased availability of tertiary education institutes could also have substantial positive spillover effects when girls with tertiary education enter the labour force as school teachers facilitating the supply of more low-cost private schools (Andrabi et al., 2008).

Literature review

This review of the literature sheds light on three issues. First, the issue of gender inequality in the labour market outcomes. The second is the household's decision to invest in education. Third, the approaches adopted in various studies establish a causal link between educational attainment and the financial returns to education.

The labour force participation rate of female graduates in Punjab between the ages of 25 and 35 is only 32% compared to that of men at 96% (Labour Force Survey, 2018). The wages of women with higher education are approximately sixty-eight percent of the wages of equally qualified men (PSLM, 2014). In ongoing work, we probed the likely causes of the gender wage gap by breaking it down into explained and unexplained gaps. Our main finding was that almost one-third of this gap can be explained by the difference in the human capital of men and women and their nature of work. The remaining two-thirds of this gap is unexplained and can be attributed to either discrimination or omitted variables (Tirmazee, 2021). Numerous explanations, such as occupational segregation (Levanon et al., 2009; Blau and Kahn, 1992), work interruptions (Epstein, 1988; Neumark and Korenman, 1992), education and training (Blau and Kahn, 2017; Becker, 2010; Mincer, 1962, 1974), temporal flexibility (Goldin, 2014) or unionization (ILO. 2018), have been advanced in the literature for the gender pay gap. In the context of Pakistan, it has been argued that the gender pay gap is because most women either work as unpaid family workers or if in paid employment they are often employed in low-skill, low-paid jobs (Khan, 2017).

This analysis is important, as the literature suggests that households respond to information regarding returns to education. For instance, Jensen (2012) provides evidence of how increasing awareness regarding potential job opportunities owing to the rapid expansion of the business process outsourcing (BPO) industry in India led to a significant rise in investment in the education of younger girls by households. Similarly, Attanasio and Kaufmann (2009) provide evidence on the significance of individual perceptions regarding future returns to schooling using data for Mexico. In their analysis to model college or school choice, they find that mothers' expectations and individuals' expectations matter for college enrollment. Similarly, in other settings where different instruments were used to provide information, such as the author's calculated returns to education (Jensen, 2010) or a short video showcasing the ways of acquiring financial resources to fund education (Dinkelman and Mart´ınez A, 2014), it is seen that households update their beliefs and react accordingly. Given how households react to information on returns to education, we believe that analysis such as ours is crucial, as it directly yields information on these returns and reflects the expectations that influence parents' and students' decisions regarding investing time, money, and effort in education.

Since our main objective in this paper is to estimate a causal link between labour market returns and human capital accumulation, we now review various approaches for estimating this causal link. The general approach in the literature for tackling the question of private returns to schooling has been an estimation of the

Mincerian wage function (Mincer, 1974), which is a simple regression linking schooling with the wages earned. The following is a simple Mincerian wage equation:

$$Ln(Earnings)_i = \beta_0 + \beta_1 S_i + \beta_2 X_i + e_i \quad (1)$$

where Ln(Earnings)i is the log of yearly earnings of person i, Xi is a vector of individual i's characteristics, and Si is the accumulated years of education. OLS yields biased estimates of the parameters of the above equation due to unobserved heterogeneity. Additionally, the classic Mincerian wage equation does not allow us to test for the heterogeneity of effects. how the observed relation between years of education and the returns to education differs across various subsets of the population. Some possible solutions suggested in the literature to address the shortcomings of the Mincerian wage equation are as follows:

First, studies have directly tried to account for the 'ability bias' by proxying for it using IQ level or test scores. However, there are always concerns regarding the extent to which these proxies accurately measure ability, as a multitude of measures for ability have resulted in past inconsistent signs for these variables (Dickens and Lang, 1993). One popular method to control innate ability has been the use of siblings (twins) (Ashenfelter and Zimmerman, 1997; Bingley et al., 2009; Bonjour et al., 2002; Isacsson, 1999; Miller et al., 1995) under the assumption that using twins or siblings allows one to difference out the innate ability since much of what determines an individual's ability is common across members of the same household, especially twins. This way, by eliminating unobserved individual ability by first differencing, one can obtain an unbiased estimator of the return to education by exploiting differences between the education levels and earnings of siblings (Krueger and Ashenfelter, 1992). However, twin studies are often criticized because between-twin differences in schooling are not randomly assigned but are instead endogenously chosen, especially when they depend upon an individual's own aptitude and ability or parental preferences regarding allocation of expenditure between different children.

A natural experiment is yet another interesting way of tackling ability bias, where an exogenous event is taken to instrument for the level of education. Some popular natural experiments have been minimum school leaving laws (Harmon and Walker, 1995; Dickson and Smith, 1995), the month of birth (Angrist and Keueger, 1991), or proximity to the school (Card, 1993a, 1999), where the probability of acquiring extra years of schooling increases/decreases due to a random occurrence of an event that is completely independent of unobserved individual characteristics.

There is another strand of literature that involves identifying an exogenous variable (instrument) that must be correlated with the education level but is not correlated with the returns to a particular level of education and unobserved ability. In this respect, family background variables such as parental education, spouse's education (Aslam, 2009; So¨derbom et al., 2006; Trostel et al., 2002), average education level of the household or birth order of an individual (Bertoni and Brunello, 2016; Kantarevic and Mechoulan, 2006) have been used as instruments in the literature. However, the issue remains that because of intergenerational transmission of ability, family background does not completely assure us of there being no correlation between unobserved ability and the family background variable at hand. Therefore, the popularly used demand-side family background variables as exogenous determinants of the level of education are often criticized by labour economists as only partially attenuating the ability bias.

Because demand-side instruments such as family background are widely criticized (Dickson and Smith, 1995), the focus has shifted to the sources of variation in schooling from the supply side, such as school leaving laws or proximity to schools. in search of identifying the source of exogenous variations in education attainment.

The availability of physical capital is often linked in the literature to human capital accumulation. For instance, Currie and Moretti (2003) use college openings as a source of exogenous variation in a mother's years of education to study its effect on birth outcomes. Similarly, Andarabi et al. (2012) use the presence of a primary school in the mother's village when she was at the age of going to school as a source of exogenous variation in the mother's years of education to study its impact on their children's time use. Similarly, in the literature on estimating the returns to education, physical capital has also been used as an instrument for educational attainment to address endogeneity concerns (Duflo, 2001; Maluccio et al., 1998; Card, 1993b).

Pakistan can be an important case study here as firstly; college openings have not been used to study the effect on educational attainment. This is especially important since Punjab has seen substantial expansion in tertiary education institutes in the recent decade, with a total of 51 universities and Degree Awarding Institutions (DAIs) exceeding 1000 as of 2014 (Higher Education Commission, 2016). Determining the impact of this increase in opportunities to acquire higher education on higher education itself can help to better understand the constraints on educational attainment.

For instance, if, despite increasing educational institutes, educational attainment does not increase, then one may conclude that other constraints such as mobility or social norms are much more binding and need to be approached first to optimize the use of resources and efforts.

This approach, therefore, lets one answer a relevant policy question, i.e., if increases in physical infrastructure create opportunities to increase human capital or not. Using physical capital as an instrument is also important from a policy point of view, as increases in human capital ultimately affect the lives and living conditions of citizens, thereby reducing poverty. There is evidence in the literature to suggest that the availability of schools positively affects school enrollment rates owing to the increased and easier access to opportunities to attain education (Khan, 2021; Mazumder et al., 2019; Lavy, 1996; Lillard and Willis, 1994). The availability of schools is also linked to improving socioeconomic conditions (Carneiro et al., 2013; Case and Deaton, 1999; Currie and Moretti, 2003). Moreover, Valero and Van Reenen (2019) show that human capital accumulation in addition to innovation is an important mediating factor between universities and regional growth.

Methodology

In this paper, we estimate earnings function 1 using the instrumental variable henceforth IV methodology. The first stage of the IV procedure is as follows:

$$\boldsymbol{S_t = \pi_0 + \pi_1 Z_i + \epsilon_i}\text{.....3. 1}$$

where the null hypothesis to be tested to confirm instrument relevance is $\pi_1 = 0$. We explain our instrument (Z_i) and the first stage (2) in the next section.

Identification strategy: IV estimation

This study makes use of a supply-side IV, i.e., the number of Arts and Science Intermediate, Degree and Post Graduate Colleges for Boys and Girls per 10,000 individuals in a district in a given year in Punjab. Punjab has recently seen tremendous growth in the number of colleges both private and public, with an increasing number of both girls and boys graduating from these colleges, as shown in table 3.1 below. This paper aims to make use of this expansion in tertiary education as a means of improving access to tertiary education for boys and girls. Moreover, these colleges are also a substitute for private colleges, thereby ensuring ease of access.

Table 3. 1 Number of Intermediate, Degree Colleges and Post Graduate Classes by Gender, Their Enrollment and Teaching Staff in Punjab

	No. of colleges			Enrollment			Teaching Staff		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Year	Total	Boys	Girls	Total	Boys	Girls	Total	Boys	Girls
2005-06	672	339	333	619	273	346	19131	10677	8454
2007-08	744	379	365	676	306	370	20255	11448	8807
2009-10	901	461	440	724	339	385	23096	12645	10451
2012-13	994	492	502	837	416	421	26312	14490	11822
2014-15	1095	543	552	937	455	482	26823	14997	11826

We calculate our instrument as follows:

$$Total\ no.of\ colleges\ per\ 10{,}000\ individuals_{sdk} = \frac{Total\ no.of\ colleges\ in\ a\ district_{dk}}{District\ population_{dk}}\ .\ 10{,}000 \quad (3)$$

where ‘d’ is any district in Punjab, ‘k’ is the year in which individual ‘i’ was in the normal age range for going to college, and ’.’ shows that the fraction is being multiplied by 10,000 to convert it into 10,000 individuals. We discuss more about k in the next section.

First Stage

To empirically test whether the expansion of tertiary education translates into a greater accumulation of tertiary education, the first stage of this analysis is a regression of years of education attained by individual *i* on the number of colleges per 10,000 individuals available in a district in year k in which individual *i* was at the age of going to college. Since we have a pooled cross-section spanning over a decade, this allows us to also include in our sample individuals who in the latest year do not fall in the relevant college-going age range, i.e., 16 to 24 years, which is the standard age range for individuals going to college. Our final sample includes individuals who fall between the age range of 16 to 32 years as one typically enters college at an age of 16. So anyone who is at this age in any of the included rounds of PSLM, i.e., 2006, 2008, 2010, 2012, and 2014 are included in the sample. Similarly, the upper bound for our sample is 32 years as anyone who is that old in the latest year of our analysis, i.e., 2014 would be 24 years of age in 2006 and would have just finished their masters. Therefore, the maximum age that our data allow us to include is 32 years of age in 2014. A complete description of our sample in tabular form is given in table 3.2. The table shows whether an individual at a particular age in a particular round of PSLM was included in the sample, depending on whether they were in the college-going age range, i.e., 16-24 years, in any of the included rounds. The highlighted cells (blue) are the age ranges from each round included in the final sample.

Table 3. 2 Sample Description

Age in 2014	Year when 24	Age in 2012	Year when 24	Age in 2010	Year when 24	Age in 2008	Year when 24	Age in 2006	Year when 24
32	2006	32	2004	32	2002	32	2000	32	1998
31	2007	31	2005	31	2003	31	2001	31	1999
30	2008	30	2006	30	2004	30	2002	30	2000
29	2009	29	2007	29	2005	29	2003	29	2001
28	2010	28	2008	28	2006	28	2004	28	2002
27	2011	27	2009	27	2007	27	2005	27	2003
26	2012	26	2010	26	2008	26	2006	26	2004
25	2013	25	2011	25	2009	25	2007	25	2005
24	2014	24	2012	24	2010	24	2008	24	2006
23	2015	23	2013	23	2011	23	2009	23	2007
22	2016	22	2014	22	2012	22	2010	22	2008
21	2017	21	2015	21	2013	21	2011	21	2009
20	2018	20	2016	20	2014	20	2012	20	2010
19	2019	19	2017	19	2015	19	2013	19	2011
18	2020	18	2018	18	2016	18	2014	18	2012
17	2021	17	2019	17	2017	17	2015	17	2013
16	2022	16	2020	16	2018	16	2016	16	2014

The first stage of this analysis is as follows:

$$S_{idt} = \pi_0 + \pi_1 Z_{dk} + \mu_d + \alpha_t + \epsilon_{idtk} \quad (4)$$

where S_{idt} are the years of education, Z_{dk} is the number of colleges per 10,000 individuals (as calculated in eq. 3) available in district d that individual i is from when he/she was at the age (k) of going to college, μ_d is the district fixed effects which are critical for us to control for any unobserved time-invariant district attributes that affect college availability and educational attainment in a district too allowing me to do a more robust test for proving the first identifying assumption. α_t is the year fixed effects to control for time-specific trends that allow me to control for any change over time in the taste or preference of individuals, e.g., increase in demand for education or more progressive thinking overtime etc.

The main hypothesis tested in the first stage is that exposure to a greater number of colleges does not affect educational attainment; H_0: $\pi_1 = 0$. We allow for correlation of errors within the district, i.e., use cluster-robust standard errors.

Instrument Validity

Instrument relevance: The proposed instrument is relevant given that these colleges are widely dispersed across the entire province, ensuring greater access to education for both girls and boys. It is important to highlight here that the very policy that guides the establishment of these colleges ensures greater access. These colleges are set up by the Higher Education Department (HED, a ministerial department responsible for higher education) to improve access to education. The criteria that are considered before setting up a college in a locality are i) that there is enough population in the area, ii) the number of students who pass out from SSC and intermediate levels from that area, and iii) land available for college building (Higher Education Commission, 2007). With a motive to set up an educational facility in every neighbourhood, these colleges make their way to localities where there is enough population to take advantage of this facility and that a college was not already present in that location.

Instrument exogeneity: To satisfy the exclusion restriction, we need to prove that other district- or community-level attributes are uncorrelated with the supply of colleges. To prove exogeneity, we need to show that increased availability of opportunities to acquire education is not reflective of better overall development of a region. The results, later on, show that for the relevant age range, the effect, for the most part, is driven by the variation in the availability of colleges even after controlling for the indicators of development. Additionally, controlling for district fixed effects allows me to control for unobserved time-invariant district attributes that may affect both college presence and educational attainment and may bias the estimated coefficient of the instrument in the first stage.

The other conjecture to make the exogeneity condition stronger relies on the assumption that the exact timing of college opening in a given district is not driven by demand for education. Therefore, the preferences or demand of citizens for greater opportunities to acquire education is not a concern here. So one can exploit the fact that the contemporaneous supply of colleges in a district is not driven by the contemporaneous demand for education but is reflective of pent-up demand as it takes time and incurring financial costs to respond to the demand for educational institutes and consequently set up an educational facility. To ensure that any time-varying trends or preferences are controlled for, year fixed effects have been included. Furthermore, the role that political influence plays here is also worth discussing. One can imagine that if in a certain district the member of the parliament from that district belongs to the opposition party, they would find it difficult to get funding/approval for a new college in the district, while if they are from the ruling party they may get funding/approval for a new college in the district even in the absence of demand. Therefore, the link between demand and the opening of a new college is weak. Therefore, the role of political connections must also be considered when considering the second identifying assumption.

Descriptive evidence from the data suggests that the private colleges (which one could assume are a product of demand) in Punjab cater to only one-fourth of the total student body that goes to these degree colleges for attaining tertiary education, and this has consistently been the case for all the years included in the analysis (Statistics of Arts and Science, 2015). However, to not be completely ignorant of the effect of demand, we do control for district and year fixed effects to account for preferences and changing trends.

Nevertheless, one can never completely rule out the fact that college openings in a district are not the outcome of demand for education and that there are endogeneity concerns in the first stage. We try to account for those concerns following Terza et al. (2008) by estimating a district-level model to account for factors that could be predicting these college openings. We estimate a district-level model with college per capita in any given year as the outcome and various district characteristics as predictors. We then use the residuals from this model in our main estimation model to address some of the endogeneity concerns.

Identifying Assumptions

Therefore, in running the first stage, my two identifying assumptions are

1. The relationship between changes in college availability and changes in educational attainment is not reflective of changes in development otherwise. This is taken care of in the analysis later by showing that the first-stage results hold only for the relevant age range that could have benefited from the increased availability of college and are robust to the district fixed effects.
2. The exact timing of college opening in a given district is not driven by the demand for education. This is taken care of by controlling for district and year fixed effects.

Second Stage

The second stage makes use of the estimated years of education from the first stage to estimate the returns to years of education. To find the gender gap in returns to education, we also include in the second stage an indicator for gender and interact the gender indicator with the years of education. The second stage specification is as follows:

$$Ln(Earnings)_{idt} = \beta_0 + \beta_1 \widehat{S_{idt}} + \beta_2 Male_{idt} + \beta_3 \widehat{S_{idt}} Male_{idt} + \mu_d + \alpha_t + e_{idt} \quad .....3.\ 2$$

where $Ln(Earnings)_{idt}$ is the log of yearly earnings of person i in district d in year t. $\widehat{S_{idt}}$ is the estimated years of education for person i in district d in year t, and $Male_{idt}$ is an indicator variable for gender. It is one for males and zero for females, $\widehat{S_{idt}} Male_{idt}$ is the interaction of $\widehat{S_{idt}}$ and $Male_{idt}$, μ_d is the district fixed effects to control for unobserved time-invariant district attributes, and α_t is the year fixed effects to control for time trends.

The main hypothesis we propose to test in the second stage is that higher educational attainment does not affect earnings; H_0: $\beta_1 = 0$. We allow for correlation of errors within the district, i.e., use cluster-robust standard errors.

Data and the Descriptive Statistics

To carry out this analysis, we have made use of a pooled cross-section of five rounds of PSLM for years, i.e., 2006, 2008, 2010, 2012, and 2014. The data for the supply of education were collected from the *Punjab Development Statistics and Statistics of Arts and Science Intermediate and Degree colleges* for the above-stated years.[1] Table 3.3 below is a brief snapshot of the data used for estimating the impact of tertiary education on yearly wages and how it differs by gender across the years included in the analysis. The table shows that men in our sample are on average older, have more years of experience, and earn more than women. Additionally, there is a higher chance that men in our sample than women are married. However, the highest education level attained by women is higher than that attained by men, a confirmation of the statistics presented in table 3.1 that girls' enrollment in tertiary education has been on the rise so much that it has been higher than that of men in recent years. All of these differences between men and women are significant at a one percent level of significance, as shown by the t values of difference in the means test. These differences between men and women are the same across all the years. The important thing to note from this table is how women are improving in terms of their prime human capital determinants in that the

[1] This data is available on the Punjab Bureau of Statistics website. http://www.bos.gop.pk/ developmentstat

difference between men and women in years of experience is shrinking over time. Second, women trying to catch up with men in terms of human capital have surpassed men as far as the years of education attained are concerned.

Table 3. 3 Summary Statistics

Variable	(1) Female	(2) Male	(3) Difference	(4) Count
Age	25.097	26.452	1.355***	12541
	(3.735)	(3.721)	(0.075)	
Experience (Yrs)	6.595	8.552	1.957***	12541
	(3.742)	(3.917)	(0.078)	
Married	0.296	0.457	0.160***	12541
	(0.457)	(0.498)	(0.01)	
Years of Education	13.553	12.926	-0.627***	12541
	(2.06)	(2.021)	(0.041)	
Real Wages	66089.781	115226.336	49,136.551***	12522
	(75601.023)	(107254.305)	(3280.801)	
Observations	3,306	9,235	12,541	

Note*:* Author's calculations using five rounds of PSLM, 2006, 2008, 2010, 2012 and 2014. 'Real wages' are computed by dividing nominal wages by the CPI index for that year. We have used 2006 as the base year. The CPI index values were taken from the World Bank database. 'Experience' is calculated as age-years of education attained-5 following Aslam (2009).

As shown in Table 3.3 above, men in our sample on average earn significantly more than women[2], and the same phenomenon is evident in the kernel density graph shown below in Figure 3.1. A look at the raw data in figure 3.1 suggests that the distribution of yearly wages for males for different levels of education peaks to the right of the series' mean compared to that of women who have a much wider distribution. It is also noteworthy that the shape of the wage

[2] It is worth acknowledging here that difference in earnings can be due to difference in work hours. Hourly wages therefore would be a better measure to observe difference in earnings. This however cannot be captured in the data that we are using and is a limitation of this study.

distribution for women changes from a bimodal to just like that of men from Intermediate to Masters. This points to the fact that there is greater inequality of wages between men and women at lower education levels. At higher education levels such as Masters, women tend to be doing much better in catching up with men. There are two lessons that we learn from these graphs: i) for all three levels of education, women outnumber men at the lower end of the distribution, which means that no matter what education level they earn less than men, and ii) just above the mean, the distribution for women is lower than men, suggesting that at the higher end of the wage distribution, women are outnumbered by men.

As the wage distribution of women is bulkier toward the lower end of the distribution and begins to decline on the higher end before the men's wage distribution declines, there is a clear indication that women earn less than men. Although the raw data indicate a gender gap in wages earned by men and women who have acquired more than ten years of education, the next section reconfirms this observation using instrumental variable regressions.

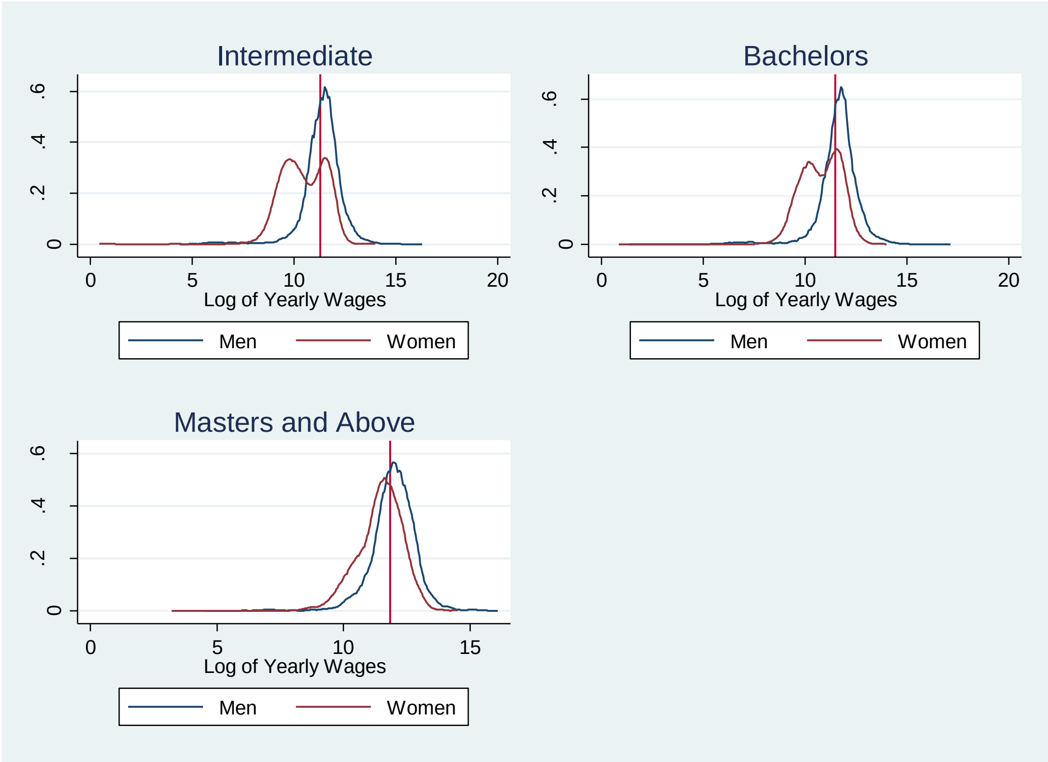

Figure 3. 1 Wage Densities by Education for Men and Women

Source: Author's calculations using various rounds of PSLM data.

Results

The results of the first stage are reported in table 3.4. One can see from the first stage results that the chosen instrument does a good job of predicting the highest education level attained by an individual. The total number of educational institutes per 10,000 individuals in a district in the year when an individual was at the age of going to college significantly affects the years of education. As hypothesized, the greater the number of tertiary education institutes the person is exposed to when they were at the age of going to college, the significantly greater the likelihood that they end up going to college and therefore attain more years of education. Moreover, we have also controlled for the unobserved time-invariance factors by controlling for district fixed effects and time-varying year fixed effects. Our argument that increasing the schooling inputs per capita improves access to education, subsequently leading to an increase in the highest level of education attained, seems to be valid (table 3.4, column 1).

To prove that the first-stage results are not driven by the overall development in a district, we ran the first stage by additionally controlling for community-level development indicators. Specifically, the development indicators included are a source of drinking water, grocery store, public transport, primary school, middle school, hospital, and a population welfare centre available within thirty minutes of the household. In column 2 of table 3.4, one can see that the instrument continues to hold its significance even now. Although the coefficient size has reduced, it is still positive and significant.

To prove that the changes in the years of education are not reflective of changes in development in general and that for our sample i-e within the given age range, additional years of education attained above matriculation are significantly affected by college availability in the district, we ran the first stage for individuals who do not fall in our desired sample age range i-e aged 16-32 in any of the included years. The logic behind doing this was to see if the relationship between years of education and the number of colleges is spurious. If it is a spurious relation, then we should see years of education increasing regardless of college presence, even for individuals who are not at the age of going to college.

Table 3.4: First Stage Regression

Dependent	*Years of Education*			
VARIABLES	(1)	(2)	(3)	(4)
Total number of colleges	4.52**	0.936*	1.31**	
per 10,000 individuals	(1.821)	(0.558)	(0.624)	
Change in the total number of colleges per 10,000 individuals				0.210***
				(0.03)
Year FE	YES	YES	YES	YES
District FE	YES	YES	YES	YES
Development Indicators	NO	YES	YES	YES
Observations	11,677	11,677	11,677	989
Mean of the dependent variable	12.86	12.86	12.86	12.54

Note: Robust standard errors in parentheses. SEs clustered by districts. Controls in the first stage include experience, experience squared, and married. The dependent variable in all the columns is years of education attained. Column (1) does not control for development indicators. Column (2) includes the development indicators. Column (3) also controls for residuals from a regression that regresses ‘Total number of colleges per 10,000 individuals’ on district characteristics, including population, public transport, primary school, middle school, hospital, and population welfare centre. Column (4) uses the ‘Difference in the total number of colleges per 10,000 individuals’ in a district over two consecutive years as an instrument. This was run for a subset of the sample who reached the age of entering college at the time of new college openings. Development indicators controlled for are access to piped water, grocery store, public transport, primary school, middle school, hospital, and population welfare centre *** p<0.01, ** p<0.05, * p<0.1

As a placebo check, we run our analysis on very narrow age bands around the upper (32 yrs) and lower (16 yrs) age cut-offs. The reason for this was to make the comparison between roughly similar groups. The comparison at the lower end of the age distribution is therefore made between individuals who lie between the age bracket of 12 to 15 years and those who fall between 16 to 19 years. However, at the upper end of the age distribution, the comparison is made between individuals who lie between the age bracket of 29 to 32 years and those who fall between 33 to 36 years. For each of these four regressions other than the basic controls included in table 4, development indicators were also controlled for. Again, the coefficient plots of these regressions are presented in Figure 3.2. Therefore, for individuals who are at the age of going to college, it can be argued safely that college presence matters. If this was a spurious result then one would see some impact in the similar groups also and that one would see human capital increasing regardless of college presence reflecting general progression in the society. Additionally, year-fixed effects have also been incorporated in generating Figure 3.2 in an attempt to control for trends that change over time, such as a taste for greater years of education.

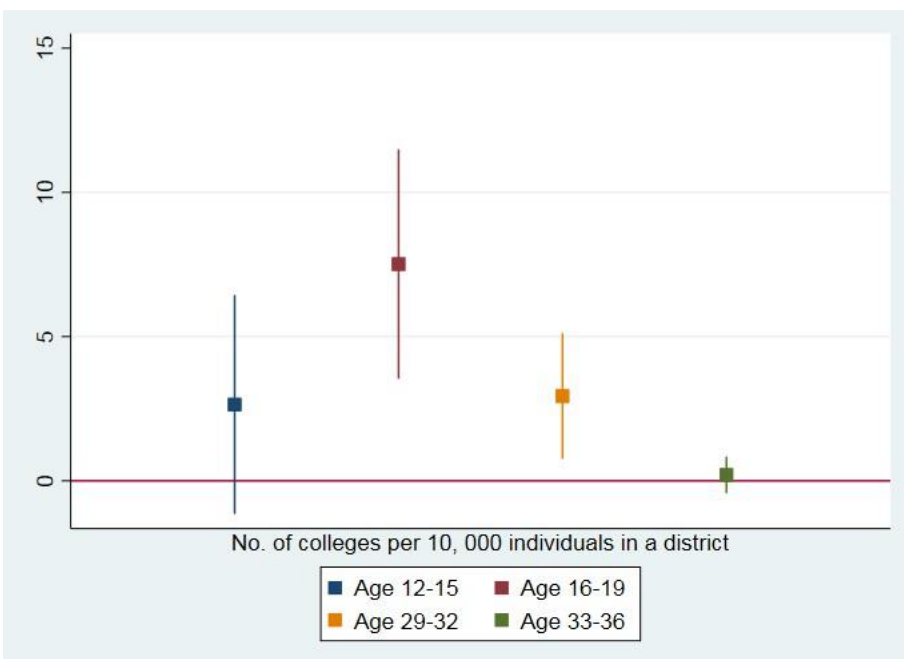

Figure 3.2: Estimates of Beta Coefficients of Number of Colleges for Tighter Time Windows

Controlling for Community Development
Note: Community development indicators controlled for are access to piped water, grocery stores, public transport, primary schools, middle schools, hospitals, and population welfare centres.

To also satisfy our second identifying assumption that college openings are not induced by the demand for education, we run two additional tests. First, following Terza et al. (2008), we estimate the colleges per capita at the district level from a regression of colleges per capita per 10,000 individuals in a district on various district characteristics and then use residuals of this regression as a regressor in our main model. This lets us address some endogeneity concerns in our first stage. The results of this model are given in column 3 of Table 3.4. We can see that even when we account for the unobserved factors that may affect both educational attainment and college openings in the first stage, we still see a positive significant first stage.

Second, as an analogous check, we also run our first stage on a subsample restricted to a narrower window of cohorts who reached college age around the opening date of each college. This lets us take care of the fact that younger women may be induced to study further when there are greater prospects of getting higher studies. With a wider band, the instrument could cause unwanted differential selection into the sample; for instance, younger women are induced to attain Matric because of the greater prospect of Inter education. Our measure of new college openings is the difference in the colleges per 10,000 individuals in a district in two consecutive years in our sample. We include in this regression individuals who are 16 years old as individuals tend to enter college at this age. The results for this subsample are given in table 3.4 column 4.

The results for the second stage show that there are positive returns to attaining tertiary education and that there is a gender gap in those returns in favor of men. The results for the second stage are presented in table 3.5. The results in column 1 show that years of education beyond matriculation significantly affect one's wage. Moreover, *Male,* the indicator for gender, shows that men have higher wages than women on average. However, an additional year of education brings a significantly greater increment in wages of women compared to those of men, as the coefficient on the interaction term of *Male* and *Years of education* is significant and negative. This result is in line with earlier findings in the literature, which suggests that as years of schooling increase, the gender wage gap tends to fall (Blau and Kahn, 2017; Blundell et al., 2000). These higher marginal returns for women could be because of the dual impact, i.e., a direct effect of human capital accumulation on returns, which is also true for men, but in addition, there is an indirect impact for women, which is due to the attenuation of the impact of discrimination, tastes and circumstances (DTC) (Dougherty, 2005).

Tirmazee (2021) confirms this finding by showing that the gender wage gap is the highest at the lowest end of the wage distribution and is contributed in large part by the unexplained gap. The inverse relation between DTC (hence wage gap) and the years of schooling could probably be because more educated women have a degree or a formal qualification that lands her in a job that makes standardized wage offers or highly educated women may be able to deal well with discrimination or may even be able to find better job openings for herself where her characteristics are rewarded fairly (Dougherty, 2005). In column 2 of Table 3.5, one can see that all of these results are robust to controlling for development indicators.

An important consideration in estimating the second stage is the possibility of differences in the quality of education imparted in girls' and boys' colleges. However, that is not worrisome, as all of these colleges, whether boys or girls, are set up by the provincial ministerial department HED under uniform guidelines and are of similar quality. As mentioned above, these colleges are cheaper, and more accessible options are made available for students who cannot afford to study in private colleges. The teaching staff recruited in these colleges are recruited through a central standard procedure and are rotated periodically between colleges. Additionally, all the colleges must meet the minimum requirements of available legal and physical infrastructure as outlined by the Higher Education Commission in PU-01 proforma for setting up higher education institutions.[3]

Table 3.5: Second Stage Regression

Dependent	*Log of Yearly Earnings*			
VARIABLES	(1)	(2)	(3)	(4)
Years of Education	0.827***	1.041**	0.863***	0.619***
	(0.080)	(0.434)	(0.283)	(0.212)
Male	1.885***	2.292***	1.958***	1.559***
	(0.140)	(0.807)	(0.523)	(0.351)
Male* Yrs of Educ.	-0.553***	-0.757*	-0.587***	-0.403**
	(0.073)	(0.410)	(0.265)	(0.204)
Observations	11,677	11,677	11,677	989
Mean	11.62	11.62	11.62	11.34
Year FE	YES	YES	YES	YES

3 https://hec.gov.pk/english/services/universities/Documents/887_HEC2_Criteria_of_university_institutions.pdf

District FE	YES	YES	YES	YES
Development Indicators	NO	YES	YES	YES

Note: Robust standard errors in parentheses. SEs clustered by districts. *** p<0.01, ** p<0.05, * p<0.1. Controls include experience, experience squared, marital status, and marital status interacted with gender. Column (2) also controls for development indicators.

Robustness Checks

Selection Correction

Next, we aim to correct for selection bias given we are dealing with a very selected sample of individuals who are in paid employment and also have acquired more than ten years of education. To correct for both selection biases, we made use of the Heckmann two-step procedure (Heckman, 1976, 1979).

Selection into paid employment

The fact that the decision to participate in the workforce for women is not random given their expected gender role they are required to look after the family and the household. The need to maintain a work-life balance may affect women's decision to participate in the workforce and conditional on participating in the workforce may also affect their choice of job, profession, or industry. There could also be some self-selection happening from the men's side if they deliberately decide to enter paid work rather than being self-employed. This possibility is equally valid for women as well. All of these decisions made by men and women are dependent upon their socioeconomic conditions and may ultimately affect the returns they earn in the labour market. The extent to which a certain level of education is financially beneficial for men and women is therefore not independent of these choices that men and women make and therefore can be expected to interact with these work-related choices to either attenuate or augment the returns to education.

Correcting for selection into paid employment involved first estimating the probability of participating in the workforce using the probit model. The exclusion restriction of the participating equation included dependent children and adults aged less than seven years and greater than sixty years, respectively, in the household. The probability of salaried employment estimated from the participating equation was used to estimate the inverse Mills ratio or the selectivity term (lambda), which was later used as one of the controls in the second stage.

Selection into higher education

Another source of sample selection bias is the fact that we are dealing with a very select sample of individuals who have more than ten years of education since a very selected group of people continue to postsecondary education in Pakistan. Although women have caught up with men in tertiary educational levels at lower levels, there is still a substantial gender gap, which means that there is a very selected group of women who enter into tertiary education.

To correct for selection into higher education, we ran a second selection function where the probability of having acquired higher education was regressed on all the controls in our main wage equation along with the average education level of the household as an exclusion restriction. This exclusion restriction does not satisfy the validity condition for use in the selection model, as family members' education affects outcomes through many channels. This is particularly an issue given that the education of the current HH is endogenous due to marriage matching decisions. [4] The probability of acquiring higher education estimated from this selection function was used to estimate another inverse Mills ratio that was also used as an additional control in our second stage.

To correct for endogeneity between years of education and wages along with correcting for the two selection biases mentioned above, we incorporate the selectivity terms (IMR1 and IMR2) as controls in the IV regression. The results for this are shown in columns 2 and 3 of table 3.6. Here, the coefficient sizes, their signs, and significance are also similar to those obtained in the simple IV regression in Tables 4 and 5. The results from this section suggest that when we correct for selection bias, our main results continue to hold; therefore, it is safe to assume for Punjab's labour market that for men and women who have more than ten years of education, additional years of education bring greater returns, but those additional years are comparatively more beneficial for women than for men, leading to a reduction in the gender wage gap at each successive level of education.

[4] A better exclusion restriction could have been the parental education (Asadullah and Xiao, 2019) but our data allows us this information for a very small subsample we therefore use the average education level of the household excluding one's own.

Table 3. 4 Correcting for Selection

Dependent	Log of Yearly Earnings Second Stage	Yrs. of Education First Stage
VARIABLES	(1)	(2)
Yrs. of Education	1.128**	
	(0.445)	
Male	2.526***	
	(0.821)	
Male x Yrs. of Educ.	-0.860**	
	(0.418)	
IMR1	-0.007	
	(0.135)	
IMR2	-0.320***	
	(0.060)	
Total Number of Colleges per 10,000 individuals		0.951* (0.551)
Year FE	YES	YES
District FE	YES	YES
Development Indicators	YES	YES
Observations	11,398	11,398

Note: Robust standard errors in parentheses. SEs clustered by districts. *** p<0.01, ** p<0.05, * p<0.1. The dependent variable in the participation eq. is salaried employment. The exclusion restriction for the participation equation is dependent on children and adults aged <7 years and >60 years, respectively, in the household. IMR1 is the inverse mills ratio calculated from this equation. The dependent variable in the selection function for selection into higher education is if individuals have acquired more than ten years of education. The exclusion restriction used is the average education level of the household excluding one's education. IMR2 is the inverse Mills ratio estimated from this second selection function.

Are the results driven by affluent districts?

There is also some a priori evidence from the data to suggest that in districts where the enrollment per capita is higher, the Human Development Index [5] is also higher for 2015. The concept of human development as defined reflects the increase in the

[5] The HDI for Punjab has been taken from the Pakistan Human Development Index report 2017

capabilities of people by providing them with an increase in opportunities and ’freedom of choice’ to avail those opportunities. The choropleth maps of the province of Punjab below show that there is indeed a correlation between the human development index (Fig. 3.3) and enrollment in higher education (Fig 3.4) across districts.

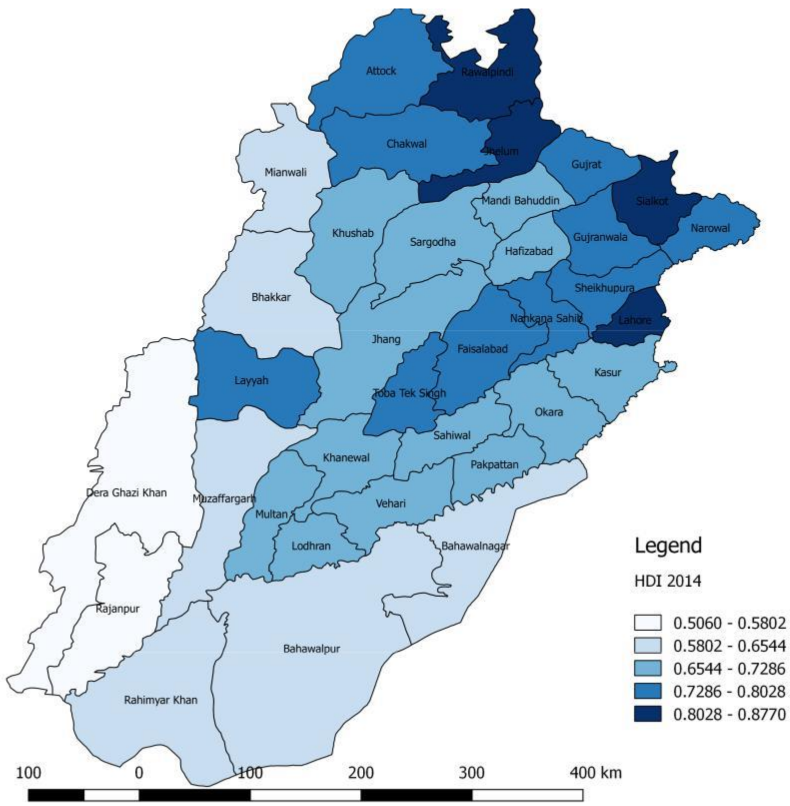

Figure 3. 2 Human Development Index, 2014

Source: Author’s analysis using HDI figures from the UNDP Human Development Index report, 2017

This is especially true for districts in the North and the center. Therefore, for instance, Rawalpindi (North) and Lahore(Center) having very high Human Development Index also have very high levels of enrollment per capita in higher education. Similarly, districts in the South, such as Rajanpur, Bahawalnagar, and Bahawalpur, and those in the West, such as Dera Ghazi Khan and Muzaffargarh, have both lower Human Development

Indices and lower enrollments per capita. Therefore, there is an indication from the data that higher human capital accumulation is correlated with better human development. This points to the need to devise ways that can ease the accumulation of human capital and provide physical infrastructure, i.e., schools and colleges are policy options available. We provide evidence that the responsiveness of human capital accumulation is higher in districts that are relatively worse off, as indicated by the HDI, making it all the more policy-relevant to invest in physical infrastructure in poorer or worse-off areas.

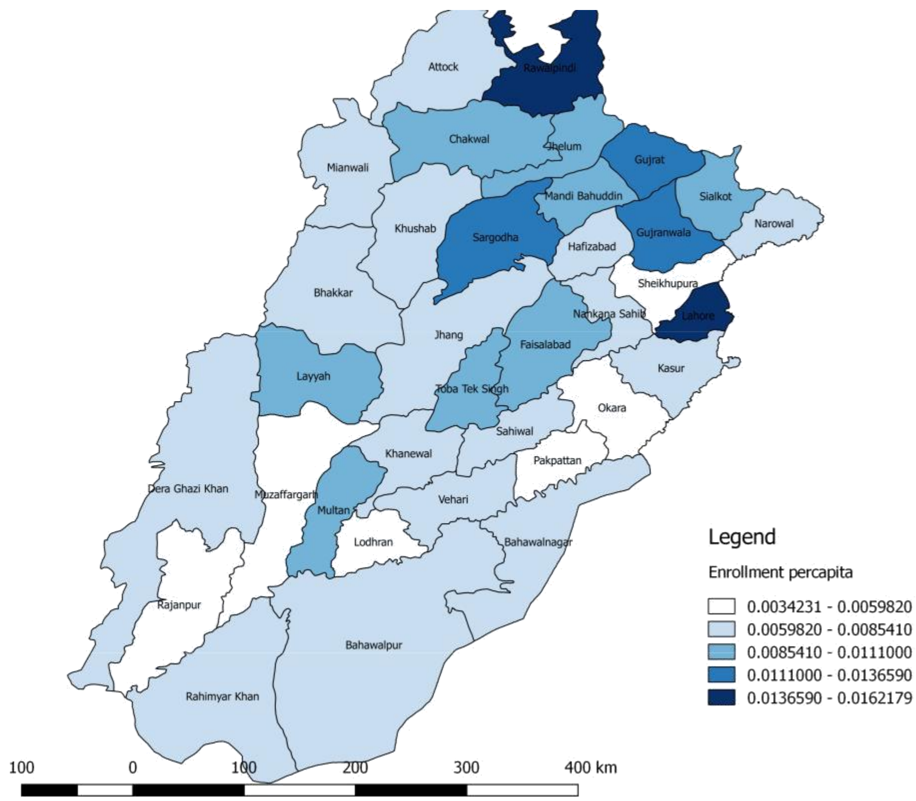

Figure 3. 3 Enrollments per Capita, 2014

Source: Author's own analysis using enrollment figures available in the Punjab Development Statistics and an annual publication of the Punjab Bureau of Statistics.

To rule out the possibility that the effect observed in the first stage may be driven by the more affluent districts where human capital accumulation and physical infrastructure are relatively abundant, we ran the analysis separately for better-off and worse-off districts. The distinction is made based on the HDI of the districts in 2014. The results for this are shown in table 3.7. The results of the first stage are significant for poorer 'Low HDI' districts, while they are insignificant for richer 'High HDI' districts. This shows that there is a greater impact of investing in physical infrastructure where the opportunities are already lagging. The results for the second stage are also significant for the low-HDI regions. The earnings for men are higher on average, but an extra year of education brings comparatively greater returns for women than it does for men.

Table 3. 5 IV-Regression: By HDI

	High HDI		Low HDI	
	(1)	(2)	(3)	(4)
VARIABLES	Second Stage	First Stage	Second Stage	First Stage
Yrs. of Education	1.074		1.322***	
	(0.800)		(0.495)	
Male	2.321		2.851***	
	(1.497)		(0.951)	
Male x Yrs. of Educ.	-0.770		-1.049**	
	(0.760)		(0.476)	
Total Number of Colleges		0.447		1.684***
per 10,000 individuals		(0.559)		(0.439)
Observations	7,075	7,075	4,602	4,602

Year FE	YES	YES	YES	YES
District FE	YES	YES	YES	YES

Note: Robust standard errors in parentheses. SEs clustered by districts. *** p<0.01, ** p<0.05, * p<0.1.

Are the results driven by men?

To rule out the possibility that the effect observed in the first stage may be driven by the boys' colleges and that the availability of colleges may increase the enrollment of boys in colleges relatively more than that of girls, we split the colleges into men's and women's by HDI levels to see the impact of each on educational attainment. To disentangle the responsiveness of girls' human capital to the presence of physical infrastructure from that of boys, we ran the IV regression by breaking down the total number of colleges into girls' and boys' colleges and taking the two as separate instruments in the first stage. The results for this are shown in table 8. Here, we see that when the colleges are split into boys' and girls' colleges, only the coefficient for girls' colleges is significant and positive in the first stage in poorer districts. The coefficient of boys' colleges is not significant in any of the regressions. In the richer districts, the significance of girls' colleges also disappears, which is an even stronger indication of the result obtained in section 6.2. College availability seems to make a difference to the marginalised group in lagging areas, which include districts in the south and west of the province. These districts are also much more conservative in their values regarding educating women let alone letting them go to a distant college in a neighbouring district or provincial capital. Therefore, increased college availability in a district may ease the mobility constraint for many women, making gender-segregated tertiary education institutes available for these girls (where other girls from similar backgrounds may come to acquire higher education degrees). The results of the second stage remain the same.

Table 3. 6 IV-Regression: Men and Women Colleges

	High HDI		Low HDI	
	(1)	(2)	(3)	(4)
VARIABLES	Second Stage	First Stage	Second Stage	First Stage
Yrs. of Education	1.024***		1.002***	
	(0.157)		(0.203)	
Male	2.21***		2.186***	
	(0.285)		(0.375)	
Male x Yrs. of Educ.	-0.716***		-0.738***	
	(0.148)		(0.190)	
Total Number of Girls' Colleges		0.0004		0.004*
per 10,000 girls		(0.001)		(0 .002)
Total Number of Boys' Colleges		0.001		0.001
per 10,000 boys		(0.001)		(0.001)
Observations	6,937	6,937	4,764	4,764
Year FE	YES	YES	YES	YES
District FE	YES	YES	YES	YES

Note: Robust standard errors in parentheses. SEs clustered by districts. *** p<0.01, ** p<0.05, * p<0.1.

Conclusion

This paper is an investigation of the gender gap in the returns to tertiary education in Punjab using the instrumental variable technique. We use exogenous variation in the expansion of the supply of higher education institutions to men and women to identify and compare the returns to tertiary education for men and women in Punjab, Pakistan. A large number of colleges in a given district can affect the probability of moving from secondary to tertiary education since accessibility improves by alleviating two constraints, i.e., the high cost of acquiring a higher degree and mobility if a college is built in one's locality. To carry out this analysis, we make use of a pooled cross-section constructed from five rounds of the PSLM survey. for 2006, 2008, 2010, 2012, and 2014.

The results of this analysis suggest that there is a significant positive relationship between years of education beyond matriculation and the earnings of individuals. Moreover, the marginal returns to acquiring one extra year of education are higher for women than for men, suggesting that gender inequality tends to fall as human capital accumulation improves. Our first-stage results profess that it is important to invest in building infrastructure to increase educational attainment. Having controlled for other development indicators and showed that this relationship holds for the appropriate age range (16-32 years, people in our sample in this age range should be of college-going age during one or more years included in our sample), we remove suspicions regarding the first stage results not being causal.

Some important policy lessons to be learned from this analysis are, first, the significance of investing in higher education both because it increases the prospects of graduates in the labour market by increasing labour market returns and because it decreases gender inequality in labour market returns. Second, the significance of investing in the physical infrastructure, such as universities or higher education institutes, facilitates the accumulation of human capital by making it less costly for households to invest in it when a higher education institute is built in their locality. Cheema et al. (2019)

discuss the glass walls hindering women from taking up training and show that once a training centre is housed in their village, it significantly increases their take-up rates.

Third, the responsiveness of human capital investment to investment in physical capital is the greatest in the less developed regions of Punjab. Therefore, the greatest returns can be achieved by targeting the expansion of educational institutes to lagging regions. Using physical capital as an instrument is also important, as an increase in human capital ultimately affects the lives and living conditions of citizens, thereby reducing poverty. There is evidence in the literature to suggest that the availability of schools positively affects school enrollment rates owing to the increased and easier access to opportunities to attain education. The availability of schools is additionally linked to improving socioeconomic conditions (Carneiro et al., 2013; Case and Deaton, 1999; Duflo, 2001; Currie and Moretti, 2003). Moreover, Valero and Van Reenen (2019) show that human capital accumulation in addition to innovation is an important mediating factor between universities and regional growth.

Fourth, a more indirect lesson that is a spin-off of the first two lessons is the spillover effects of investing in physical infrastructure, i.e., The government, by establishing tertiary education institutions in less developed regions, could promote the growth of private low-cost high schools in the area, as graduates from higher education institutes enter the labour market to increase the supply of teachers at primary and secondary levels of schooling. This is possible because of an increase in the supply of school teachers graduating from these tertiary education institutes (Andrabi et al., 2008).

There are some important directions that we feel this work could be extended in, that are currently either beyond the scope of this study or because of data being unavailable we are unable to delve deeper in. The first important direction for this work to head in is to determine which subject streams or fields tend to reduce the gender gap in the returns to tertiary education the most. Second, the distance to a tertiary education institute is a better reflection of improvement in access and could be a better instrument. In our case, our data do not allow us to capture the distance from a household to a college. Another important dimension that this work could be extended in is to see while tertiary education is expanding what is happening to the quality of the higher education being imparted across different institutes and what implications could this have for the gender gap in labour market outcomes. Last, the fate of graduates depends heavily on the balance between supply and demand. An interesting extension of this analysis could be to determine how much of the results are driven because of the expansion of access or because of the expansion of the demand for graduates in the labour market.

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4. Paper III: Encouraging Female Graduates to Enter the Labour Force: Evidence from a Role Model Intervention in Pakistan

Introduction

Countries across the developing world, and in particular in South Asia, have low female labour force participation rates.[1] Even though Pakistan has gender parity in tertiary enrollment, labour force participation rate of female graduates at 25.9% is almost a third that of the male graduates (Labour Force Survey, 2018). Yet, many women express a desire to work (Field and Vyborny, 2016; Ahmed et al., 2020). Transport, social norms, household dynamics and access to job opportunities may be significant barriers which keep women from being gainfully employed (Field et al., 2010; Heath and Mobarak, 2015; Field and Vyborny, 2016; Erten and Keskin, 2018; Jayachandran, 2020). Internal barriers in the form of lack of same-gender role models, mentors and peer support can be important determinants of labour market outcomes for women (Riise et al., 2020), though they receive less attention in literature (McKelway, 2020). Role models and mentors, in particular, can reduce 'stereotype threat' and influence aspirations (Kofoed and McGovney, 2017; Breda et al., 2018; Mansour et al., 2018; Porter and Serra, 2020; Lopez-Pena, 2020).

In this paper, we test if a low-cost, motivational nudge in the form of stories of female role-models can encourage female graduates from low-income households to increase labour force participation. We conduct a randomised control trial which is low-

[1] Female labour force participation is 36% in Bangladesh, 35% Sri Lanka, 22% in Afghanistan, 83% in Nepal, 22% in Pakistan and 20% in India (World Bank, 2020). Urban female labour force participation in Pakistan at 11.4% is almost one-third of the male labour force participation (Cho and Majoka, 2020).

cost and easily scalable, with 2500 female undergraduate students in 28 female only public colleges in Lahore, Pakistan. We alleviate some of the external constraints by giving the entire sample information about Job Asaan, a job-search portal that also provides support with CV making and interview preparation. Half of the sample is then individually and randomly selected to watch a 10 minute video showcasing real-world female role models, gainfully employed, from a similar socio-economic group as the students, followed by a brief discussion with the enumerator on the key messages of the video. These role models are meant to encourage a growth-mindset in the students, motivating them and by acting as a ‘representation of the possible’ (Porter and Serra, 2020). The other half of the sample students form the placebo group who also watched a video of a similar length but on an unrelated topic.

The role model intervention led to a higher growth mindset (Blackwell et al., 2007) in the treated group as compared to the placebo group immediately after the video was adminis-tered. We find students in the treated group were significantly more engaged with the video, scoring higher on an ‘absorption’ index (Banerjee et al., 2019). Given the relatively short duration of the this initial interaction, we reinforced the key messages of the video three months after the intervention. Treated students remembered the names and occupations of role-models before this reinforcement at three months, and in surveys conducted eighteen months after first watching the video.

We collected high frequency data on job search efforts and outcomes, conducting 3 follow-up surveys over a period of 18 months after the intervention[2]. The 18 month follow-up was a phone survey conducted right after the COVID-19 induced lockdown in March 2020 where we collected information both about the situation before the lockdown in February and after it in May 2020, i.e. 15 and 18 months after the intervention, respectively.

In our sample, 13% are searching for a job before the COVID-19 lockdown, a percentage that drops to about 5% after the lockdown. The treatment does not impact the likelihood of looking for a job, hours of job search, the likelihood of having read a job advertisement or of using any informal, formal or online platform, over the study period.

We do not find any effects of the intervention on the likelihood of working at 9, 12 or 15 months after the intervention. We can rule out results being driven by differential attrition and low statistical power. At 18 months after the intervention, which coincides with a nation-wide lockdown due to the COVID-19 pandemic, students in the treatment group are 4.7 percentage points more likely to be working, which is 24% higher than the placebo mean of 20.1%.[3] However, the treated group are not significantly more likely to be working from home, of being employed full-time, or earning above median sample wages at 18 months.

[2] Attrition is balanced across the treatment and control group. We present results for the unbalanced panel. The results for a balanced sample of 1444 respondents are similar and are provided in the Online Appendix C (Appendix 2).

[3] Note that this placebo mean of 20.1% is post the COVID-19 induced lockdown. Before the lockdown, the likelihood of working was higher: 34% in the placebo group, which is in line with national statistics for this age-group and education level.

We investigate possible mechanisms by exploring heterogeneity. Specifically, we use k-means clustering and find support for two groups in our sample – a 'low-income-education' and a 'high-income-education' group, with the students in the former group coming from households with significantly lower incomes and parental education levels than the latter. The average effect of the treatment on the likelihood of working at 18 months is driven almost entirely by an effect of about 11 percentage points for students in the 'low-income-education' group. This group is significantly more likely to report that a primary earner in their household have lost their job or have had to shut their business and report being stressed about loss of income in the household due to the COVID-19 pandemic. This may be a possible mechanism for their higher likelihood of working.

A recent study closely related to ours is by McKelway (2020), who shows that psycho-social discussions designed to engender self-efficacy can lead to significant improvements in female labour force participation in India. In contrast, we find null impacts before the onset of the pandemic, which may be attributable to a relatively lighter-touch nature of this intervention compared to the intensive and repeated interactions used in McKelway (2020)

Our study speaks to two broad strands of literature. First, we add to literature that studies the impacts of aspirational stories from peer groups on adolescent behavior (Appadorai, 2004; DuBois et al., 2011; Ray, 2006), local female leadership (Macours and Vakis, 2014) and social inclusion (Doel, 2010), as well as role model effects in influencing behavior towards divorce, fertility and domestic violence (Jensen and Oster, 2009; La Ferrara et al., 2012). We contribute to this literature by looking at the effect of real world role models on a yet unexplored outcome: encouraging labour force participation of young female graduates. In doing so, we also contribute to an evolving broader group of studies that investigate the role of psychological interventions in fostering hope; improving health outcomes, academic achievement and labour market prospects; and impacting earning differences and other important life outcomes (Heckman and Rubinstein, 2001; Duckworth and Seligman, 2005; Heckman and Kautz, 2012, 2013; Kautz et al., 2014; Duckworth et al., 2019; Ashraf et al., 2017; Bhan, 2020; Resnjanskij et al., 2021).

Second, this paper also relates to the literature that investigates barriers to labour force participation and tests interventions that alleviate these constraints. Socioeconomic background, information on available jobs and workseekers' skills can be significant determinants of entry into the labour market (Humphrey et al., 2009; Jensen, 2012; Carranza et al., 2020; Caria et al., 2020); however, studies show modest impacts of job search assistance and skills training on employment and wages (see McKenzie (2017) for a review). Search assistance and training programs, in particular, can suffer from low enrolment (Cheema et al., 2012); high cost (Adoho et al., 2014; Abebe et al., ming); and often require specific targeting to be effective (Abebe et al., 2020). Further, while job search platforms can assist in reducing information frictions, they fail to reduce search costs incurred by job applicants, or change their self-beliefs (Wheeler et al., 2020). In this study we provide evidence on a low-cost intervention that can complement conventional training and assistance programs to promote employment. We can infer from our results that this intervention was insufficient to alleviate binding constraints faced by women in the labour market, though it did prove to be effective for those who experienced high stress during the pandemic.

Experimental setting and sample

Setting

The province of Punjab (Pakistan) enjoys high female enrollment rates with at least 44% of women in urban areas having attained at least higher-secondary (grade 12) education. In tertiary education, enrolment rates are lower, at approximately 9% but there is gender parity - with enrolment rates at 8.5% for women compared to 9.6% for men (World Economic Forum, 2020). At the same time, labour force participation rate among female graduates aged between 25-35 is 35%, only one-third of that of the men (90%) (Labour Force Survey, 2014). As the second largest city of the country and provincial headquarter, Lahore is an important policy centre of Pakistan. The critically low FLFP of Pakistan is also despite the availability of a large number of jobs. For instance, at any given point in time there are on average 1800 job openings advertised on Rozee.pk (the largest online job portal of Pakistan) in Lahore alone, with an average of 20 new job postings added daily.

There are 34,000 students enrolled in the district of Lahore alone, half of whom are women, providing us with a large population for drawing the study sample. Educational institutions are often segregated in Pakistan due to social and cultural norms. We limit our sample colleges to women-only colleges in the city of Lahore. We exclusively focus on students with liberal arts majors, across 28 public colleges in urban areas of Lahore, Pakistan. Figure A1 in the Appendix 4.1 shows the location of these colleges across a population map of the city.

Focus group discussions with 100 female undergraduate students in public colleges in Lahore, Pakistan confirm that women face a range of impediments consistent with those identified in the literature in participating in the labour market. Nearly a third mention informational constraints and issues with travelling to work, but a much larger proportion - approximately 60% of the sample, expressed concerns about navigating social norms, women's mindsets[4], and lack of confidence and family support. In spite of these substantial barriers to working, nearly half expressed a desire to be working even after 3 to 5 years of graduating. A third of the sample (31%) viewed their mothers as their role models, yet only 6% of the students have working mothers. While students in this sample have access to the internet and may be exposed to famous, successful women, it appears that they may not have had exposure to relatable role-models who are successful in the labour market.

Assuming 29 percent labour force participation rate in Punjab (this is the participation rate for women between 18 to 36 years with a higher education degree calculated using data from Labour Force Survey, 2014.) as the base rate, the proposed design allows us to detect a 5.5 percentage point effect size with 88 percent power at the 5 percent significance level.

[4] This pertains to questions asked during focus group discussions from the students regrding the extent to which they think that that working and earning is the responsibility of male members of the family while women are meant to be the homemakers and care takers in the household.

Sample

We conducted a baseline survey with 2,499[5] female final year undergraduate students between October 2018 and February 2019. Of them, 1,224 (49%) were randomly assigned to the treatment group. The intervention was reinforced between February-May 2019 (intervention reinforcement). The respondents were interviewed again between, August-September 2019 (follow-up 1), December-January 2020 (follow-up 2) and then finally between May to June 2020 (follow-up 3). Figure 4.1 displays the study timeline and Appendix A in Appendix 4.2 provides details of each round.

	Baseline	Intervention reinforcement	Follow-up1	Follow-up 2	Follow-up 3 (R)	Follow-up 3
Time since baseline		3 months	9 months	12 months	15 months	18 months
	Oct'18-Feb'19	Feb-May'19	Aug-Sep'19	Dec'19-Jan'20	Feb'20	May-Jun'20
					Mar'20 (COVID lockdown)	
	N=2499	N=2184 (12.6%)	N=2189 (12.5%)	N=1746 (30.2%)	N=1614 (35.5%)	N=1614 (35.5%)

Figure 4. 1 Timeline of Activities

Notes: In Figure 1 we show the timeline of activities; specifying time since baseline for each survey round, and the corresponding months of activity. Note that at Follow-up 3 we ask about retrospective outcomes just before the onset of the pandemic (15 months since baseline, denoted by 'R') and current outcomes (18 months since baseline). 'N' refers to the sample size with attrition rate at each data collection round reported in parentheses.

Descriptive Statistics

[5] Assuming 29 percent labour force participation rate in Punjab (this is the participation rate for women between 18 to 36 years with a higher education degree calculated using data from Labour Force Survey, 2014.) as the base rate, the proposed design allows us to detect a 5.5 percentage point effect size with 88 percent power at the 5 percent significance level.

The sample is well-balanced across a range of individual and household baseline characteristics for the full baseline sample (Table 4.1).[6] The sample belongs to households with an average monthly income of approximately USD 315 which is close to the provincial average of USD 368 for urban households (HIES, 2015).[7] The majority live in households that are owned by their family. The households are large, with 7 members on average.

The proportion of the sample that desires to work after they graduate is very high at 83%. The majority want a salaried job with only 2% who want to set up an enterprise. The average response is that it is highly possible for an educated woman like them to work. Four-fifths of the sample (80%) thinks there would be hindrance in finding a job, with one-third mentioning difficulties in travelling for work, and a fourth about permission from family/in-laws. Consistent with the focus group discussions, students are most likely to identify mothers as their role models[8], yet a very low proportion of their mothers currently work. A small proportion of individuals at the baseline are married (8%).

A fifth of the sample are already doing some part-time work as they are studying, mostly giving tuition at home and those who work, earn about USD 81.2 a month on average (the table reports the unconditional mean). On average, the students spent about 4.3 hours studying[9] and approximately 3 hours doing housework every day. Not surprisingly, given the baseline was conducted nearly a year before graduation, there is

[6] Column 4 in Table 4.1 reports observations for each baseline characteristics, all of which were collected before treatment implementation. A similar table for the balanced sample is provided in Appendix 1 Table C.1. For some outcomes, we have missing values due to respondent refusal to answer. The refusal rates are uncorrelated with treatment status (Results are available upon request).
[7] We use the exchange rate at the time of the study baseline in 2018, USD 1= PKR 123.12, throughout the paper.
[8] Note that this question, and those on whether the respondent was currently working mentioned in the next paragraph, was added towards the end of the baseline survey so we only have 121 observations for them.
[9] This is the number of hours spent studying outside college and does not include college hours.

very little job search at baseline (less than 5% in the last 4 months) with an average of less than 1 hour spent on this.

Table 4. 1 Descriptive Statistics

Variable	(1) Placebo	(2) Treated	(3) Difference	(4) Obs
Panel (a): Household characteristics				
Monthly household income (USD)	312.892	319.991	7.100	2,283
	(206.632)	(225.340)	(9.043)	
Dummy: Own house	0.836	0.823	-0.012	2,494
	(0.371)	(0.382)	(0.015)	
Household size	6.533	6.595	0.061	2,499
	(1.957)	(1.928)	(0.078)	
Father's years of education	9.462	9.186	-0.276	2,499
	(5.013)	(5.171)	(0.204)	
Mother's years of education	7.691	7.407	-0.284	2,499
	(5.077)	(5.173)	(0.205)	
Dummy: Mother works	0.084	0.068	-0.016	2,432
	(0.277)	(0.252)	(0.011)	
Panel (b): Own characteristics				
Dummy: Want to work after graduation	0.835	0.837	0.002	2,497
	(0.371)	(0.370)	(0.015)	
Dummy: Married	0.080	0.085	0.005	2,499
	(0.271)	(0.279)	(0.011)	
Hours of study per day	4.332	4.389	0.057	2,493
	(2.948)	(3.057)	(0.120)	
Hours of housework per day	2.969	2.892	-0.077	2,498
	(2.283)	(2.269)	(0.091)	
Dummy: Searched for a job	0.047	0.045	-0.002	2,499
	(0.212)	(0.207)	(0.008)	
Hours of job search in the last 4 months	0.249	0.231	-0.019	2,497
	(2.216)	(1.702)	(0.079)	
Monthly personal income (USD)	28.460	25.885	-2.575	2,456
	(87.811)	(82.146)	(3.435)	
Observations	1,275	1,224	2,499	

Note: Columns (1) and (2) show the mean value of the variable in the row for the placebo and treatment sample, respectively. Column (3) reports the difference in means between the placebo and treated sample ($***p < 0.01$, $**p < 0.05$, $*p < 0.1$); and column (4) displays total number of observations for each variable. Standard deviations are reported in the parentheses. Panel (a) provides outcomes measures at the household level and Panel (b) provides average characteristics of the respondent.

Attrition

Figure 4.1 displays the round-wise rate of attrition in parentheses. We were able to successfully interview 87.4%, 87.5%, 69.8% and 64.5% respondents at the time of reinforcement interven-tion at 3 months, and followup surveys 9, 12 and 18 months after the baseline, respectively. Reassuringly, attrition is not related to treatment status – there is no statistically significant difference between the attrition rate in the treatment and the control group in any of the rounds of data collection.

Table 4.2 displays the attrition by treatment status. In columns 2, 4, 6 and 8, we include controls for baseline covariates, as well as the interaction of these covariates with the treatment status.[10] Attrition is correlated with some individual characteristics collected at baseline (before treatment implementation): in different rounds, we find attrition to be predicted by the household living in own house, father's education, mother's work status, and whether the respondent looked for a job before intervention implementation (Appendix 4.1 Table A.1). However, the interaction of covariates with treatment status are largely insignificant, with some exceptions. For instance, mother's work status at 9 months and mother's work status and hours of job search positively and significantly predict attrition in the last survey round at 18 months. However, a joint test of significance reveals treatment status and the group of individual covariates interacted with treatment status do not predict attrition in the last round and is only marginally significant at 9 months. In addition, attrition is not predicted by work status and does not arise because of respondents finding work and refusing to participate in subsequent rounds. Results are available in the Table B.1 (Appendix 4.2).

[10] All regressions control for the college a student is enrolled in. College does not predict attrition: the F-statistic from a test of joint significance of college and treatment status interaction has a p−value of 0.971, 0.756, 0.626 and 0.958 for surveys 3, 9, 12 and 18 months after baseline. Results available upon request

Our main analysis utilizes data from the full, unbalanced panel. We show robustness of our main results in two ways. First, we report Lee (2009) on all estimates of main treatment effects. Second, in Appendix C in Appendix 4.2, we re-run the analysis using a balanced panel of 1444 women interviewed in all rounds.

Table 4. 2 Attrition by survey round

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Months since baseline	**3**	**3**	**9**	**9**	**12**	**12**	**18**	**18**
Treated	0.016	0.112	0.007	0.091	0.009	0.174	0.008	0.097
	(0.013)	(0.078)	(0.013)	(0.084)	(0.018)	(0.114)	(0.019)	(0.116)
Controls	N	Y	N	Y	N	Y	N	Y
p(F-stat)		0.13		0.09		0.70		0.30
Mean	0.13	0.13	0.12	0.12	0.30	0.30	0.35	0.35
Observations	2499	2183	2499	2183	2499	2183	2499	2183

Note: Columns (1)-(2) report attrition from the intervention reinforcement survey (3 months after the baseline), columns (3)-(4) from follow-up 1 (9 months after the baseline), columns (5)-(6) from follow-up 2 (12 months after the baseline), and columns (7)-(8) from follow-up 3 (18 months after the baseline). Columns 2, 4, 6, and 8 report results from a saturated regression with controls for household characteristics (monthly household income, dummy for own house, household size, father's yeas of education, mother's years of education, and dummy for mother works) and respondents' own characteristics (dummies for if wants to work after graduation, and is married, hours of study and housework per day, dummy for if searched for job, hours of job search in the last 4 months, and monthly personal income) and the interaction of these controls with the treatment dummy. All covariates are collected before the intervention is implemented. Observations in columns 2, 4, 6 and 8 are lower due to missing observations in baseline characteristics. A detailed version of this table displaying all observable covariates in columns 2, 4, 6, and 8 can be found in Table A.1. 'p(F-stat)' refers to the p-value of F-Statistic from a test of joint significance of the interaction of treatment status and baseline characteristics. Robust standard errors are presented in parentheses. 'Mean' refers to the average level of attrition in each round. * p < 0.10, ** p < 0.05, *** p < 0.01.

Design

Intervention Motivation

The study intervention is motivated by Blackwell et al. (2007) and Carol Dweck's work on the importance of growth mindset (Dweck, 2007, 2012) in improving performance in the classroom (Paunesku et al., 2015; Yeager et al., 2016, 2019), social settings (Walton and Wilson, 2018), and reducing stereotype threat (Aronson et al., 2002). A growth mindset encourages individuals to view intellect as malleable with sustained efforts to learn, to be open to challenges, and to endure in the face of adversity. Growth interventions address beliefs about intellect and challenge the view that intellect is fixed. This view may be particularly important in settings where individuals are led to believe they may be naturally lacking talent or skills required to succeed. One such setting is that of women facing a host of social, cultural and psychological barriers to their labour market participation. Beliefs about success in the face of adversity can influence their goals and extent of perseverance in the face of difficulties (Locke and Latham, 1990).

A second source of motivation for the intervention comes from literature on human psychology that argues that human beings primarily model their behaviour on others with the human mind influenced by beliefs and actions of those around us (Lieberman, 2014). Indeed, recent evidence suggests representation and role models can be very effective in changing the beliefs and actions of others around them (see, for instance, Jensen and Oster (2009); Chong and Ferrara (2009); La Ferrara et al. (2012)). Real-world role models have been found to positively affect aspirations and occupation choices (Beaman, 2012). For instance, face-to-face interaction with women who have majored in male dominated fields has encouraged female undergraduate students to do the same (Porter and Serra, 2020). Others have shown similar success in changing beliefs and performance using inspirational videos (Bernard et al., 2014) and movies (Riley, 2017).

The intervention video combines elements from these two strands of literature by exposing women to relatable, real-world women who have successfully handled challenges faced in the labour market. The aim is to encourage a growth mindset (Dweck, 2012) by emphasizing that women can also secure gainful employment and have successful careers if they persist in the pursuit of employment. In the intervention video, the challenges role models faced, and how they successfully handled those challenges with effort and perseverance in the face of hardship is shown. This is aimed to encourage a growth mindset, drawing inspiration from the experiences of role models seen in the video. Individuals with a growth mindset are expected to be motivated, and hence, better equipped to handle the challenges of the labour market and succeed in realizing their labour market goals.

Intervention Details

The intervention consists of a documentary video on real educated women from public colleges in Lahore who have been 'successful' in the labour market, in that they have secured a job and are satisfied in their current jobs. We collabourated with the administrations of sample colleges to identify successful alumni. We identified 5 women, all of whom were public college graduates belonging to a similar socio-economic group as the sample respondents. These five women (the names of whom cannot be disclosed due to confidentiality) belonged to different occupations: lawyer, curator at a library, lecturer at a public university, assistant curator at an art gallery and police officer. We chose a mix of professions, including both common and rare occupations for women, such as a lecturer and a police offer, respectively. We show female role-models because it has been found that women tend to respond better to same gender role-models (Lockwood, 2006).

We worked with ContentCreators, a Lahore-based private media company, to film interviews with the five role models for the documentary. Before the interviews were filmed, the research team met with each of the role models in separate ice-breaking session to explain to them the purpose of these interviews. For making the final documentary, the media company used notes from the ice-breaking sessions to draft the script and prepared the documentary by meeting the role models once again to film their responses to our listed questions. The focus of the interviews were on four dimensions: i) challenges faced by the women in acquiring an education and a job, ii) how they overcame these challenges, iii) how their families feel about their success and, iv) a piece of advice or a lesson they learnt from their struggles that they would like to share with young women. We also included in the documentary where possible clips of family members to show family support and how they felt about the struggles and the eventual success of the role model.

The interviews were then combined into a 10-minute long video highlighting specific themes across the interviews with compelling background music, voice-overs and shots from women's workplace and homes. The video was not just a question and answer session with the role models but a well-integrated narrative highlighting the need for self-belief, confidence to face problems and to not run away, focusing on goals, dreaming big, working hard and remaining steadfast to achieve these dreams. It also highlighted that it is possible to balance household and work responsibilities with shots of women with their children at home.

It is worth mentioning here that when interviewing the role models, we specifically wanted to highlight the constraints identified by the college students to enter the labour market during the focus group discussions conducted with 100 currently enrolled students in April-May 2018, and to show real life examples of women like them who have managed to overcome these challenges and are now successfully employed. The documentary emphasizes that setbacks are an opportunity to learn; that the process of learning is enjoyable in itself; and that economic empowerment can help both their standing in the household and household welfare.

The video screening was followed by a two to three minutes' discussion on the content of the video to reinforce the message. The discussion script is in Appendix D of Appendix 4.2. The respondents were reminded what they can learn from these women, the importance of persistence and perseverance highlighted, the possibility of balancing work and family life and that they need to step out of their comfort zone if they want to achieve anything. At the end, they were encouraged to think about what they need to do in order to be successful. The key messages of the videos were reinforced only to the treatment group by the enumerators approximately three months later.[11] The students were shown the videos individually on a tablet. We decided to not involve the families of these students in order to reduce the possibility of backlash from family members (e.g., as hypothesized in McKelway (2020)), and in order for the intervention to be scaled-up in colleges at low-cost. Before we rolled out the study, the intervention video was piloted with 25 out-of-sample college students to see if the video and the survey could be

[11] We had originally planned to have experimental variation in whether a student is treated once or twice but after the initial intervention, we decided that given its light touch nature, we will not be powered for this analysis. Therefore, we proceeded with giving everyone in the treatment group a repeat intervention message. The pre-analysis plan for the follow up rounds was lodged before any data was analysed to reflect this. With the placebo group, we only administer a followup survey at 3 months.

conducted with each student within a reasonable length of time during college hours. Students in the placebo group watched a video of the same length as the treatment group. This was deliberately chosen to be on a completely unrelated subject to the treatment.[12] The data collection for this study took place in five rounds as shown in the study timeline (Fig 4.1).

Focus group discussions revealed that students are concerned about the lack of preparedness to enter the labour market – 65% did not know how to make a CV and only 13% believed teachers could help in making one, 32% said they lacked guidance related to job applications. 23% highlighted being provided with information on job openings and 38% on interview skills training as a key way to help them. In order to address these constraints, all students, in both the treatment and placebo arm received information about 'Job Asaan'; an existing job search portal that connects job seekers with employers in metropolitan Lahore. That is, all the sample was provided with similar access to information on existing jobs in Lahore. A 'Job Asaan' flyer with the link to register on the portal along with other basic information regarding the 'Job Asaan' services printed on it was handed over to all participants (see Appendix E of Appendix 4.2).

The intervention cost is at USD 9.77 per respondent. This is comprised of fixed cost of video development and the post cards given at follow up for a total of USD 4.45 and field costs associated with implementation of the intervention of USD 5.22 per respondent.[13] The development costs consists mainly of a fixed cost of video

[12] Link to the documentary shown to the placebo group: https://www.dailymotion.com/video/x35wwat.
[13] Note that we do not include cost of researcher time input into the development of the videos.

development, with per unit costs expected to fall for larger samples. The implementation costs include salaries of the enumerator team. Part of these unit costs, such as those incurred in piloting and training, can also be expected to be fixed and decrease for larger samples. Appendix B in Appendix 4.1 provides details of costs incurred.

Sample selection and treatment assignment

The protocol used for sample selection and treatment assignment at the individual level is as follows:

1. We requested the college administration for a list of students enrolled in the final year of the bachelors' program.
2. On the basis of enrollment data from step 1, we identified the proportion of the total working sample to be drawn from each college.
3. We randomly selected 70% of the working sample to be the actual sample and kept 30% as a replacement sample to be contacted if a sample student is not located or if she refuses to participate in the survey.
4. We collected all survey data on tablets using SurveyCTO (www.surveycto.com). At the time of the baseline data collection, our software assigned the student to either the treatment or placebo group, with equal probability.

Empirical Strategy

Our basic estimating specification is:

$$y_{it} = \beta_1 . T_i + y_{i0} + \mu_c + \epsilon_{it} \tag{1}$$

where y_{it} is an outcome variable, T_i is a dummy variable capturing exposure to treatment, y_{i0} is the outcome of interest measured at baseline if available, μ_c denote college fixed effects. The main hypothesis we propose to test is that exposure to the treatment i.e. female role-models has no effect; $H_0 : \beta_1 = 0$.

We estimate the impact of the intervention immediately after the intervention was administered on a measure of 'absorption' and on growth-mindset. At 9, 12 and 18 months after baseline, we look at two key outcomes: job search and likelihood of working. Job search is a binary indicator equal to 1 if the woman looked for work in the last month. In line with recent studies from developing country contexts (e.g., Franklin (2018); Abebe et al. (2020); Groh et al. (2016a,b)), we take a broad definition of 'work' as being gainfully employed for pay. This includes full time and part time work, salaried work or day labour, and other work such as providing tuition to students for where income is fixed monthly or per hour. In what follows, we present results using data on an unbalanced panel of women interviewed in each survey rounds. The results for the balanced panel interviewed in all survey rounds are qualitatively similar and available in Appendix C of Appendix 4.2.

The analysis follows a pre-analysis plan. We depart from it in the following ways: i) We had specified a job search index created out of a binary variable measuring likelihood of searching for a job, and additional variables capturing job search intensity. For ease of exposition, we focus on the binary indicator in the main analysis but we show treatment effects on the additional job search intensity measures in Appendix 4.1 Table A.3. (ii) In the trial registry, we specified looking at academic performance as an intermediary outcome. We were not able to collect this data due to COVID-19 induced closure of colleges in March 2020. Colleges were reluctant to disclose final year exam marks from the previous academic year once they re-opened.

Results

Intervention engagement and retention

We first test if the video was effective in engaging the respondents. Measures at baseline were reassuring: 97% of the respondents said they found the video to be interesting, 99% believed the video documented the experiences of real women, and 65% of the sample felt they could relate to the women in the video (Table 4.3). This number is

Table 4. 3 Intervention engagement and retention, at baseline and first followup (treated group only)

	Observations	Mean	SD	Min	Max
Panel A: baseline					
Video was interesting (%)	1222	97.1	16.7	0.0	100
Videos captured ‘Real Stories’ (%)	1211	99.3	8.6	0.0	100
Related to characters (%)	1219	65.1	47.8	0.0	100
Panel B: First followup (4 months after baseline):					
Remembers video (%)	1059	99.1	9.7	0.0	100
Correctly answers quiz qs 1 (%)	990	61.5	48.7	0.0	100
Correctly answers quiz qs 2 (%)	993	71.7	45.1	0.0	100
Discussed video with family (%)	1048	73.2	44.3	0.0	100
Reflected on video’s message (%)	1059	79.5	40.4	0.0	100

Note: This table presents data on respondent attention and absorption at baseline, i.e., immediately after the intervention was implemented; and recall at the time of the first followup, 4 months after the intervention was first implemented. In Panel A, Video was interesting is defined as an indicator variable for if the respondent finds the video somewhat or very interesting, Videos captured ‘Real Stories’ is an indicator variable for if the respondent thought the role models in the videos were real, Related to characters is defined as an indicator variable for if the respondent reports completely relating with at least one character. In Panel B, Remembers video is an indicator variable for if the respondent reports remembering the video, Correctly answers quiz questions are indicator variables for if the respondent correctly answered questions about specific aspects of the role model stories, discussed video with family and reflected on video’s message are indicator variables for if the respondent answered yes.

very high as expected as we chose the role models such that they came from similar socioeconomic backgrounds as our main sample.

Three months later, at the time of the Intervention reinforcement, 99% of the treated respondents remembered having seen the video. Two-thirds of them were able to correctly answer questions about the video; and an even larger proportion reported having reflected on the messages of the video and having discussed it with members of their family. At 18 months after baseline, 88% of the treatment group still remembered watching the video, with two-thirds also correctly remembering the profession of at least one of the role models. Overall, survey measures reveal a relatively high degree of respondent attentiveness.

We test if respondent engagement and reaction to the videos differ by treatment status through two immediate checks: One, we construct a transportation index to test if respondents watching the treatment video were more engaged with the video than the respondents who viewed the placebo video. This index is constructed using Principal Component Analysis (PCA) on four items to capture ‘absorption’, following Banerjee et al. (2019). The 4 items include whether the participant was distracted by surrounding activities, by their own thoughts, if they were affected emotionally, and/or intrigued to learn more about the characters in the video. We find that participants who watched the role model video were ‘transported’ to a greater degree, with average transportation index almost two times higher than the placebo group mean of -0.332 (column 1, Table 4.4). This difference, reassuringly, is driven by the treatment group being more emotionally engaged and wanting to know more about the characters in the video as compared to the placebo group.

Second, we quantify the extent to which the treatment video was able to engender a growth mindset. We do this by using a validated Implicit Theories of Intelligence scale (Blackwell et al., 2007), implemented immediately after they watched the assigned video. This involved aggregating responses on a series of statements aimed at assessing the extent to which participants consider their ability is fixed or malleable. We find that the role model video led to a significant increase of around 0.1 standard deviation in the growth mindset of treated women. This indicates that immediately after watching the video, treated respondents were more conducive to acquiring knowledge and less likely to believe that they are limited by their intrinsic level of intelligence than respondents who watched the placebo video (Table 4.4).[14] These immediate checks reveal that the role model video was successful in engaging respondents and in changing their mindset, at least immediately after they first watched the video.

Table 4. 4 Post intervention treatment effects

	(1) Transport index	(2) Growth mindset
Treated	0.677*** (0.049)	0.068* (0.040)
Observations	2491	2491
Mean(placebo)	-0.332	-0.034

Note: This table displays results from an OLS regression testing treatment effects on outcomes measured after intervention implementation. 'Transportation index' is an index created using Principal Component Analysis (PCA) measuring respondent's absorption with the video, following Banerjee et al. (2019). 8 respondents did not answer one of the questions on which this index is based and were dropped from the analysis. 'Growth mindset' is a standardized index created out of Implicit Theories of Intelligence scale by Blackwell et al. (2007). 'Treated' is a binary variable equal to one for respondents who viewed the role model video; 0 for those who viewed the placebo videos. 'Mean (placebo)' is the

[14] The effect on having a growth-mindset is no longer significant at the first follow-up three months later. On the other hand, we find significantly higher 'locus of control' (Rotter, 1966) among treated respondents three months after the intervention, though this effect also dissipates over time. Results are available in the Table B.2 (Appendix 4.2).

average value of the dependent variable for the placebo group. Robust standard errors are presented in parentheses. $* p < 0.10$, $** p < 0.05$, $*** p < 0.01$

Effect on labour market outcomes after graduation

Next, we test if the treatment video was successful in changing respondent behaviour with respect to their job search efforts and work status. We collect information on these outcomes at 9, 12 and 18 months after baseline. At 18 months, we collect retrospective information from before the onset of the COVID-19 pandemic, providing us with data at approximately 15 months after the intervention.

In line with national statistics, a third of all graduates (35%) were working before COVID-19 pandemic related lockdown, in February 2020. This number drops to 22% in May 2020, after the lockdown. Amongst all women who are working, 65% are tutors - of which (81%) provide tuition from home earning on average USD 59.28. A fifth (20%) are employed in other, full-time salaried work earning a higher salary of USD 105.57, 13% are working part-time work and a small proportion (3%) are self-employed, providing beauty, stitching or embroidery services. They earn an average income of USD 77.15.

Fig 4.2 panel a presents the intent-to-treat effects on the likelihood of searching for a job among the full, unbalanced sample of women in the study.[15] Results show that treated women are not significantly more likely than the placebo group to engage in job search during the study period. At 9 months, immediately after they graduated, there was some indication of higher likelihood of job search (2 percentage points more) in the treated group but in subsequent periods the effect sizes are smaller. Our confidence

[15] We look at a number of other dimensions of job search and do not find any impact of the treatment (Appendix 4.1, Table A.3).

intervals show that we can rule out large effects in all periods except at 9 months where the upper bound of the 95% confidence interval is 0.05. We consider if we are under-powered to detect small effects by constructing Minimum detectable effect (MDE) sizes following Haushofer and Shapiro (2016). Even the largest effect size at 9 months of 0.020 is half that of the MDE size for that period (Appendix 4.1 Table A.2, columns 1-4). In addition, there results are robust to attrition – the lower and upper Lee bounds are insignificant at all time periods.

Treatment effects on work status are shown in Figure 4.2 panel b. The effect size is very small initially, but increases over time. In the initial period, our effects are much smaller than the MDE size (Appendix 4.1, Table A.2, columns 5-7). However, at 18 months, women in the treated group are 4.7 percentage points more likely to be working as compared to the placebo group, an effect that is statistically significant.[16] This coincides with the Covid-19 related lockdown when it appears that the labour market may have become more challenging. We see a drop in overall employment rates for our sample across all occupations, including home tuition, with no difference by treatment status ($p - \text{value} = 0.36$). A decrease in household incomes may have also have driven this effect. We discuss this in Section on heterogeneity.

All role models shown in the intervention were working outside the home. Once we condition on working, we do not observe a significantly different likelihood of work from home (Appendix 4.1, Table A.4, Panel a) or of being employed in full-time work (Appendix 1, Table A.4, Panel b) between the treated and placebo women. We also test if treatment led to greater likelihood of working in higher income jobs. We do this by analysing if they are more likely to be earning more than the sample median monthly income of USD 81.21. We find some indication that this is the case 15 and 18 months

[16] These results are robust to differential attrition. The upper and lower bounds are insignificant before the last follow-up at 18 months, after which they range from 4.5 to 4.9 percentage points and are statistically significant.

after the intervention. However, the effect is only marginally significant at 15 months (Appendix 4.1, Table A.4, Panel c).

We had phone follow-up discussions with the sample to understand why we see effects on work status but not on job search. Women in our sample revealed a strong preference for work at or near their homes, consistent with evidence found in literature in similar settings (Said et al., 2021; Cheema et al., 2019). Therefore, it is likely that our measures of search, which relate to formal jobs, do not capture efforts made to find such jobs. Indeed, two-thirds of those employed at the last follow up are working as tutors and their job search efforts involve using informal networks to find students in the neighbourhood to teach.

Heterogeneity

Heterogeneity by household income-education status

Our sample is quite homogeneous in terms of respondent aspirations, future plans, age and other characteristics. This is not surprising since the sample is selected from women enrolled in public colleges in a major urban city in Pakistan, and not representative of a broader population. Nevertheless, we do observe certain household characteristics along which there is considerable heterogeneity at baseline. For instance, one-fifth of the sample have fathers who have studied up to grade 5; fathers of another third of the sample have at least 10 years of education. We explore whether the impact of the treatment varied by the participants' personal, parental and household characteristics.

This analysis was not specified in our pre-analysis plan. For this reason, we employ an unsupervised machine learning technique, k-means clustering, to define sub-groups in our sample, rather than selecting the dimensions along which we define sub-groups ex-post. We classify participants into groups on the basis of the following baseline characteristics: age, parental education, household income and family size.[17]

(a) Job search (b) Work status

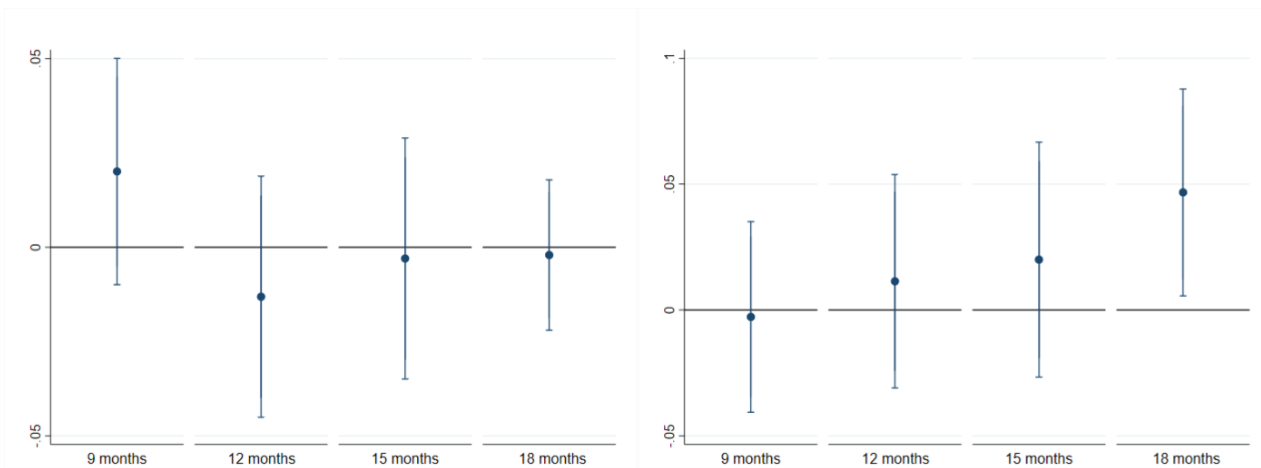

Figure 4. 2 Treatment effects on job search effort and work status over time (Unbalanced panel)

Note: This figure displays treatment effect coefficients from an OLS regression run separately for each survey round. 9, 12, 15 and 18 months refer to the number of months since the baseline and intervention when the dependent variable was measured. The dependent variable (in panel a) 'Job search effort' is a binary indicator equal to 1 if the woman looked for work in the last month. The dependent variable (in panel b) 'Work status' is a binary indicator equal to 1 if the woman in engaged in any type of work, whether full or part time. The coefficients shown are for the 'treated' variable which is a binary indicator equal to one for respondents who viewed the role model video; 0 for those who viewed the placebo video. The average value of the dependent variable for the placebo group in panel a is 0.17, 0.15, 0.13 and 0.05 at 9, 12, 15 and 18 months respectively. The number of observations is 2,189, 1,746, 1,614, and 1,614 at 9, 12, 15 and 18 months respectively. The corresponding average value of the dependent variable for the placebo group in panel b is 29%, 28%, 34% and 20%. The number of observations is 2,186, 1,744, 1,614, and 1,614 at 9, 12, 15 and 18 months respectively. A table version of this figure with Lee bounds can be found in Appendix 1 Table A.2.

[17] We standardise these variables to avoid high variation in a variable from being over-weighted in the analysis. At baseline, 216 respondents did not report household income. Instead of making assumptions about the nature of missing values and doing imputations, we drop these individuals from this analysis. Reassuringly, the likelihood of missing data at baseline is balanced across the treatment and placebo groups.

The k-means clustering algorithm finds groups in the data with similar characteristics, minimizing the squared Euclidean distance and ensuring that the sum of the distances for observations in a cluster are minimized. The aim is to find the 'natural' groups of students with similar characteristics at baseline. In order to identify the optimal number of clusters, we adopt the methodology followed by Riley (2020), using both the sum of within-cluster distance and the pseudo-F index. Based on these measures, we find support for two groups among our respondents. These are de-fined across the income and education of the student's parents. In subsequent analysis, we refer to these groups as low-income-education and high-income-education households, with a sample of 919 and 1364 women, respectively. We have good balance across the treatment and placebo groups within these two sub-groups (Tables B.3 and B.4 of Appendix 4.2).

Women from the low-income-education household category belong to households where the average monthly household income and father's education are lower relative to women from the high-income-education households (Table B.5 in Appendix 4.2): the average household income in low-income-education households is USD 261.54 compared to USD 355.85 in high-income-education households, the average education of fathers in the low-income-education households is 3 years relative to 5 years in the high-income-education household category. Mothers are more educated on average in the high-income-education group, with an average of 11 years of education, relative to 3 years of education for mothers in the low-income-education group. The high-income-education households are smaller and the likelihood of the respondent's mother working is twice in the high-income-education group as compared to the low-income-education group. The low-income-education group could relate more (28%) to the constraints faced by the role models as compared to the high-income-education group (23%).

The effect of the treatment on the high-income-education group is very small and insignificant in all periods (Fig 4.3 panel b). In the low-income-education group there is a similar pattern initially, with some indication of higher (but not significantly different) likelihood of working at 15 months. At 18 months, after the start of the COVID-19 pandemic, they are approximately 11 percentage more likely to be working compared to women in this sub-group who were assigned to watch the placebo video (Fig 4.3 panel a). These findings suggest that the average effect on work status at 18 months discussed in the previous section may be driven by the low-income-education group. In part, this may be due to the treated low-income-education sub-group being 9.2 percentage points more likely to respond that they are often or very often stressed ($p - \text{value} = 0.02$) compared to the treated high-income-education group about loss of own and household income due to the COVID-19 pandemic. Further, a primary earner in their household is 8.9 percentage points more likely to have lost their job or have had to shut their business due to the pandemic ($p - \text{value} = 0.018$).

Further, consistent with the null average effects on job search and potential reasons discussed, we do not find any significant difference at 18 months in job search effort (Fig 4.4 panel a & Fig 4.4 panel b). We also do not find any resulting heterogeneity in the likelihood of earning above median income (i.e. greater than USD 81.21 per month; Table B.6 (Appendix 4.2)).

Heterogeneity by enrollment status

We have information on enrollment in a masters (postgraduate) degree at 9, 12 and 18 months. We find that a little over a third of our sample proceed to enroll in a master's degree after graduation. This may be motivated by a desire for better job market outcomes: at baseline, respondents expected masters graduates to be able to earn twice as much as undergraduates. Four out of the five working women showed in the treatment video had an advanced degree. While their degrees were not explicitly mentioned (except for one), there were references to them being highly educated and this could also be inferred from their jobs. On the other hand, the treatment may have pushed the women to join the labour force immediately, at the cost of pursuing a master's degree. Therefore, we test if the treatment led to a differential likelihood of enrollment in a master's program. We find null treatment effects on the likelihood of enrollment (Appendix 4.1, Table A.6 panel a).

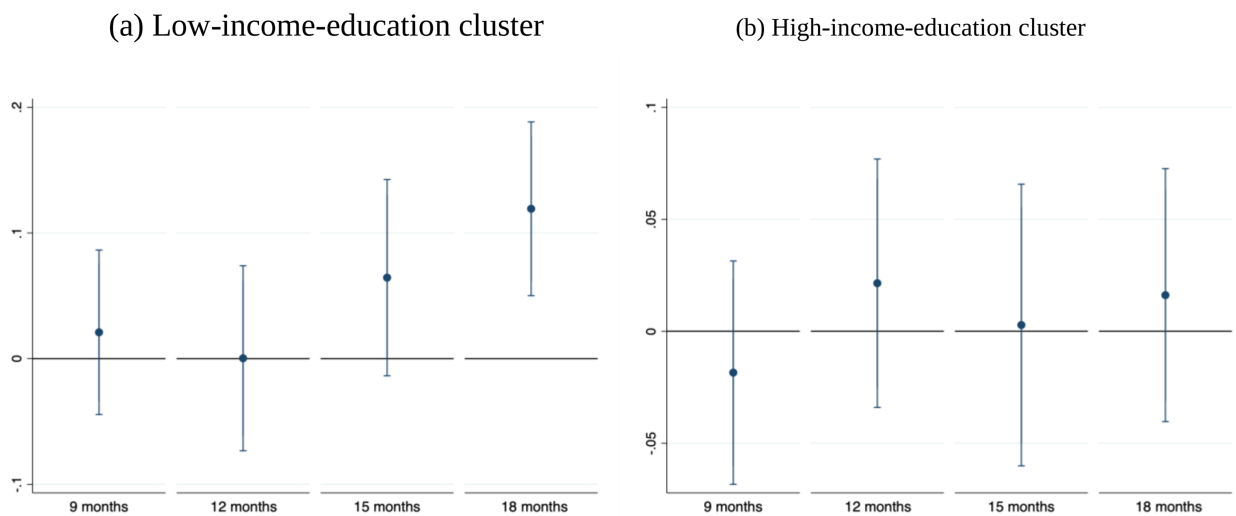

Figure 4. 3 Treatment effects on work status over time

Note: This figure displays treatment effect coefficients from an OLS regression run separately for each survey round. 9, 12, 15 and 18 months refer to the number of months since the baseline and intervention when the dependent variable was measured. The dependent variable 'Work status' is a binary indicator equal to 1 if the woman in engaged in any type of work, whether full or part time. The coefficients shown are for the 'treated' variable which is a binary indicator equal to one for respondents who viewed the role model video; 0 for those who viewed the placebo video. Panel a reports results for the low-income-education sample (defined in the section of heterogeneity) and panel b for the high-income-education cluster sample. The average value of the dependent variable for the placebo group in panel a is 0.314, 0.324, 0.319 and 0.167 with a sample size of 800, 620, 580, and 580 at 9, 12, 15 and 18 months respectively. The corresponding average value of the dependent variable for the placebo group in panel b is 0.279, 0.253, 0.343 and 0.225 with a sample size of 1,195, 969, 887, and 887 at 9, 12, 15 and 18 months, respectively. A table version of this figure with a fully interacted model is in columns (5) to (8) in Appendix 1 Table A.5.

(a) Low-income-education cluster (b) High-income-education cluster

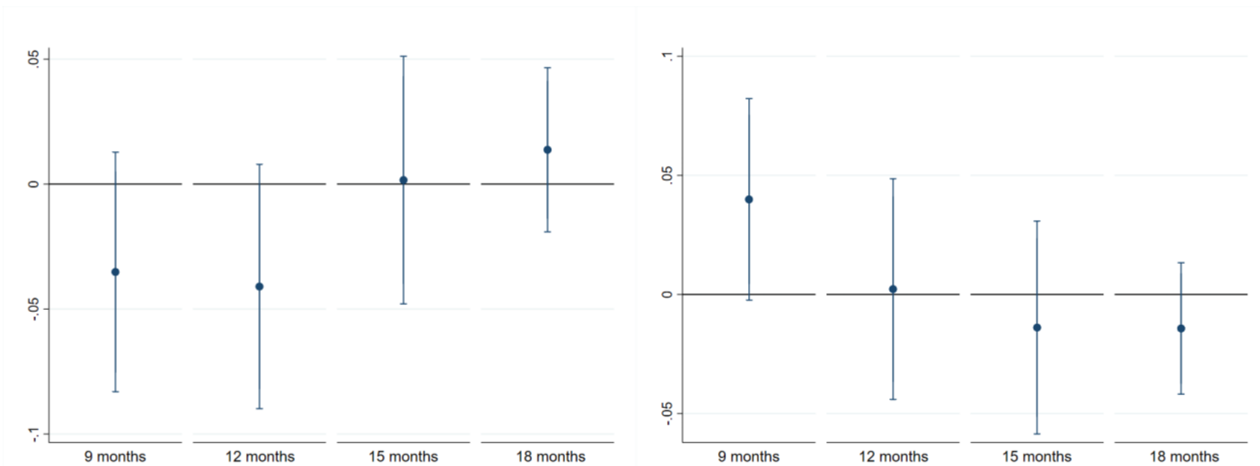

Figure 4. 4 Treatment effects on job search effort over time

This figure displays treatment effect coefficients from an OLS regression run separately for each survey round. 9, 12, 15 and 18 months refer to the number of months since the baseline and intervention when the dependent variable was measured. The dependent variable 'Job search effort' is a binary indicator equal to 1 if the woman looked for work in the last month. The coefficients shown are for the 'treated' variable which is a binary indicator equal to one for respondents who viewed the role model video; 0 for those who viewed the placebo video. Panel a reports results for the low-income-education sample (defined in the section on heterogeneity) and panel b for the high-income-education cluster sample. The average value of the dependent variable for the placebo group in panel a is 0.178, 0.141, 0.104 and 0.028 with a sample size of 802, 622, 580, and 580 at 9, 12, 15 and 18 months, respectively. The corresponding average value of the dependent variable for the placebo group in panel b is 0.178, 0.168, 0.143 and 0.056 with a sample size of 1,196, 969, 887, and 887 at 9, 12, 15 and 18 months, respectively. A table version of this figure with a fully interacted model is in columns (1) to (4) in Appendix 1 Table A.5.

We explore treatment effects amongst women who are not currently enrolled in graduate studies, and are therefore available to work. Despite no treatment effects on likelihood of enrollment, this is analysis with a selected sample and was not pre-specified and is based on status measured post-treatment, and so should be interpreted with caution. The treatment effects on job search and work status are reported in the Appendix 4.1 Table A.6 only for women who were not currently enrolled in a master's program at the time of that survey round. We find no treatment effects on job search in all periods and on work status at 9 and 12 months. Consistent with the average effects, among women who do not pursue graduate study, we observe a significant effect of the 'role models' treatment intervention on being gainfully employed post-pandemic only at 18 months after the intervention (Appendix 4.1 Table A.6 panel c, column 3). Treated women have a 6 percentage points greater chance of having a job which is approximately 30% higher than the placebo group mean.

Heterogeneity by other characteristics

We also test if graduates who had a social science major - such as economics, finance, psychology and mathematics, are more likely to be working than graduates majoring in humanities (e.g. language and religious studies). We find no clear indication of heterogeneity in treatment effects for job search or likelihood of working by the subject they majored in (tables B.7 and B.8 (Appendix 4.2))[36].

[36] We restrict the sample to students only in the Humanities. These majors equip students with general skills and variation in subject choices within Humanities therefore may not affect labor market prospects much. For instance evidence from India suggests that enrollement in science subjects is associated with greater earnings compared to enrolling in humanities (Jain et al, 2021). Evidence from Indonesia suggests no siginificant differential in labor market outcomes of individuals who pursue general secondary education versus those who pursue technical vocational education (Chen, 2009).

We also consider if the treatment effects varied by the college the respondent studied in. Findings suggest that treatment effects on working 18 months after the baseline may vary by the college the student was enrolled in at the timof the baseline: The p − value (F-test) of a test of the joint significance of treatment and college interactions is 0.01. Given the choice of college is not random but a function of respondent characteristics, such as parental income, this finding is in line with the overall patterns observed in heterogeneity by income and parental education discussed in the section on heterogeneity by household income-education status. We had pre-specified a series of analysis on other dimensions of heterogeneity such as Big 5 personality assessment.[37] We find no significant effects on the job search or work status by these characteristics at any of the follow-up rounds.

Additional outcomes

Marital Status

Our data allows us to determine if the marital status of the respondents changed over the study time period, though we do not have data on the match quality. At baseline, as shown in Table 4.1, there was no significant difference in the marital status of respondents in the placebo and the treatment group. At the last follow up, 18 months later, the proportion of respondents who are married have increased but this proportion does not vary significantly by treatment status: 11.7% of the treated individuals are married at endline compared to a slightly higher 14.3% in the placebo group.

Job Asaan Database Outcomes

[37] These results are available in the PAP report, available here.

Respondents were informed about Job Asaan, a job search portal, on the day the baseline survey and intervention were administered. All respondents agreed to complete the first stage of signing up for the service at baseline, which was done for them by the enumerator. They had to subsequently complete a second sign-up process that required logging on a link and providing information on expectations around jobs. At this second sign-up stage, the Job Asaan portal collected detailed information related to applicants' job preferences and provided information on the different services that Job Asaan offers.

We were able to match 1,087 of our 2500 respondents with the Job Asaan database. 236 of these 1,087 respondents had fully completed the second stage of the sign-up. We find no effect of the treatment on the likelihood of completing the second sign-up stage (Appendix 4.1 Table A.7). In the data reported on the Job Asaan portal, respondents in our sample who completed the second signup expect to take 4 months to find work, for a monthly wage of USD 263.93 with no significant difference between the treatment and placebo group. Consistent with self-reported measures, we don't find any effect of the treatment on various measures of job search in the Job Asaan administrative data.

The Job Asaan portal also collects data on applications made for job matches on the portal. Treated women in the low-income-education group are 14 percentage points more likely to apply for a job using the Job Asaan portal than the women in the low-income-education placebo group, though this difference in statistically insignificant. While we interpret these results with caution due to the small sample size, it is reassuring that the patterns we observe in the Job Asaan data are consistent with patterns from self-reported behaviour from survey data.

Spillover Effects

Information spillover is possible with individual level randomization. It is even more likely when information provided to the treated group is easy to communicate - for instance, information about a job site that has a large listing of jobs. In contrast, we expect ex-ante that motivational nudges and psychological constructs (like aspirations and motivation) would be more difficult to pass on in comparison to objective information about job search sites and resume-making thus reducing the spillover of aspirational and motivational 'nudges'. However, if spillovers do occur, they can bias the measurement of treatment effects towards zero, while increasing the cost effectiveness of the intervention by diffusing the benefits, if any, of the intervention to a larger group of people at little or no cost.

We follow methodology proposed by Banerjee et al. (2019) to estimate spillover effects by following the behavior of network friends. We asked all participants, in both the treatment and placebo groups, to name five 'network' friends from the same college, with whom they communicate regularly. During the follow-up survey at 9 months, we also surveyed the network friends to observe affect (if any) of the treatment on network friends.

We were able to successfully contact 503 of these network friends spread across all colleges surveyed[38] We find that friends of treated group are 9 percentage points more likely to enrol in a master's program as compared to friends of placebo group (Appendix 4.1 Table A.8). While we do not find any treatment effect on the likelihood of enrolling

[38] Out of these, 286 were friends with the respondents in the placebo group and 217 were friends with the treated respondents.

in a master's program for the main study sample (shown in Appendix 4.1 Table A.6), for the sub-sample for whom we have data on friends, the main sample women are significantly more likely to be enrolled (by 20 percentage points, p = 0.019; table not shown but available upon request). Hence, we are cautious in interpreting the spillover results since these seem to be friends of a 'selected' sample.

We look at spillover effects on three job related outcomes: if they have created a CV, if they searched for a job in the last month and if they had a job. We find no evidence of a spillover effects of the treatment on work status or job search effort (Appendix 4.1 Table A.8). We also try to disentangle results by the main respondents' personal and household characteristics as we have done in the section on heterogeneity and test if friends with those in the low-income-education group are more likely to be affected by their treated friends (Appendix 4.2 Table B.9). We see no heterogeneity by this aspect.

Conclusion

In this paper we test if an intervention involving role models can encourage female graduates from low-income households to enter the labour force. We find that participants who were shown a 10 minute video and a brief discussion showcasing successful working women from similar socio-economic backgrounds – role models - demonstrated an immediate improvement in 'growth mindset' and high recall of the video content four and eighteen months later. However, we do not find any meaningful improvement in the likelihood of looking for work or of working post-graduation up to 15 months after the intervention. We estimate and show Lee bounds to rule out differential attrition and ex-post MDEs to address concerns about low statistical power.

We find a moderate increase of 4.7 percentage points in the likelihood of working 18 months after the intervention among the treatment group. The 18 month results coincide with a nation-wide lockdown, when the labour market conditions may be expected to be different from normal. This effect is being driven by women belonging to households with lower parental education and household incomes. A possible mechanism is that these women were significantly more stressed about lost household income due to the COVID-19 pandemic.

The lack of average treatment effects (before COVID-19) are consistent with recent literature that highlight binding constraints to female labour force participation, such as limited safe transport options, restrictive social norms (McKelway, 2020; Cheema et al., 2019; Field and Vyborny, 2016), lack of interpersonal skills and the ability to interact effectively with family member's opposition (McKelway, 2020; Dean and Jayachandran, 2019) that the intervention tested in this study did not directly target. In addition, it is possible that the light-touch nature of the intervention was insufficient encouragement for women to overcome these constraints.

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5. Conclusion

This thesis is an investigation of the labour market outcomes of women in Punjab. It is imperative to study the labour market outcomes and understand their determinants to tackle gender inequality which is evident in almost all socio-economic outcomes. The very low female labour force participation rate and significant disparity in the returns to working in the labour market are worth exploring if the solution to gender disparity is to be sought.

Chapter 2 is an investigation of the gender wage gap of individuals with more than 10 years of education in the district of Punjab. We use two rounds of the PSLM data for Punjab to study the dynamics of the gender wage gap and its constituents i.e. the endowment effect and the coefficient effect which we estimate using the conventional Oaxaca-Blinder methodology (Oaxaca, 1973). This particular study is a contribution to the literature on wage gap decomposition for two reasons. Firstly, gender wage gap decomposition analysis using a pooled cross-section of two rounds of a data set that covers a decade has not been done. Our analysis not only lets us study the contribution of each of the individual observed and unobserved components of the wage gap but it additionally informs the reader of how the wage gap and its components have trended over time. This kind of analysis is especially helpful in the context that we are considering in this study which is despite the improvement of prime human capital determinants of women over time their wages do not seem to be converging with those of men over time. It, therefore, lets us explore the data further to pin down factors that could explain this trend over time.

Secondly, the other major contribution of this analysis that makes it different from other studies done on this topic for Pakistan is that other studies that make use of wage decomposition analysis only go to the extent of estimating the contribution of each of the components for a single year for a particular region but none go beyond it to understand what plausible factors which when controlled for may affect the relative magnitudes of the unexplained gap and the explained gap. Since one can only hold those factors responsible for the wage gap that one incorporates in the specification, those that are left out go into the unexplained category. So the real challenge with decomposition analysis is to be able to pin down a factor that may help to increase the percentage contribution of explained part and reduce the size of the unexplained gap. In our analysis, we can achieve that by including occupation and industry-specific gender ratios. This study is the first of its kind for Pakistan in that respect. We add these ratios to see if the fact that most women with tertiary education in Punjab tend to enter the ’Social and Personal Services Industry’ as education and health professionals. So we hypothesize that given women tend to populate only a handful of jobs, their supply relative to men for these limited jobs is higher. This excess supply of women for limited jobs coupled with a very low elasticity of substitution since women (because they prefer certain job characteristics like temporal flexibility, work environment, the gender ratio at their workplace etc.) tend to enter a very narrow set of jobs their wages in comparison to men tend to rise slower thus widening the gender wage gap. Indeed, in our base model where we correct for only selection into paid employment, results show that when the industry/occupation gender ratios are controlled for unexplained gap shrinks. However, when we additionally also control for selection into higher education, controlling for gender ratios gives mixed results.

The third chapter is an investigation of the returns to tertiary education and the gender gap in these returns using the IV estimation technique. This analysis is also done using five rounds of PSLM data i.e. 2006, 2008, 2010, 2012, and 2014. To find the returns to tertiary education we use the number of intermediate and graduate degree colleges at the district level in Punjab as a source of exogenous variation in the years of education attained by an individual. In estimating our first stage of the IV estimation we make two identifying assumptions to establish causality between the supply of tertiary educational institutes at the district level and years of education attained by an individual.

Our first identifying assumption is that the relationship between changes in college availability and changes in educational attainment is not reflective of changes in development in general. As one could imagine that accumulated years of education and opportunities for acquiring an education are both indicators of development therefore they may both be trending simultaneously to show a significant first stage without there being actual causation. To account for that, we do two things i) in our first stage we control for several community-level development indicators and ii) we show that our first stage is only significant for a relevant age range i.e 16-32 (an age bracket for whom the supply of colleges matters) and does not show significant results for individuals who lie above and below this age range.

Our second identifying assumption is that the exact timing of college opening in a given district is not driven by demand for education since higher educational attainment may also be driving increased college opening. This is not possible since it takes time and financial resources to set up a college we argue that contemporaneous demand for education cannot affect the contemporaneous supply of educational institutes. Also one cannot rule out the role of political influence which may affect the supply of colleges even in the absence of any demand for them. This proposition is further strengthened by the fact that almost 75% of the total population of students going to post-secondary classes enrol in public colleges. So the demand affecting college supply is not too much of a problem otherwise private colleges would be housing a greater number of students. To further strengthen our results of the first stage we also control for district fixed effects that lets us control time invariant district-specific attributes. We also control for year-fixed effects since it is a multi-period study to control for changing tastes and trends.

Our results for this paper reveal two very interesting findings which have some policy relevance too. Firstly, the first stage is significant for the entire sample, when we breakdown our sample into high and low HDI districts we show that results of the first stage are primarily driven by the less developed districts of Punjab This means that college opening has the greatest impact in the lagging regions where the opportunities to acquire education are already very scant. The other major finding of this analysis is that in the second stage we show that although men's wages are higher than those of women on average, the marginal return to one extra year of education for women beyond matriculation is higher for women than for men. This could be the reason why the enrollment gap between men and women beyond matriculation and especially at graduate level has shrunk.

Chapter 4 documents a randomised controlled trial done to understand the impact of motivational nudges on the job search effort and eventually labour force entry of undergraduate students enrolled in the last year of their Bachelor's degree. This experiment was conducted with 2500 female undergraduate students enrolled in the 28 female public degree colleges in urban Lahore. This particular study adds to the existing literature that demonstrates the positive impact of inspirational stories on outcomes such as local female leadership, social inclusion or other social outcomes such as divorce, fertility etc. This study contributes to the literature by showing inspirational stories of students who graduated from these same colleges. Our intervention is a 10-minute documentary that shows the lives and struggles of five role models who despite facing several challenges in their lives during their student life and even after graduating managed to make it through these challenges and are now successfully employed. These role models work in a diverse range of occupations and belong to similar socio-economic backgrounds as the girls going to these colleges do. We use graduates of the same colleges as role models to make them relatable and be a 'representation of the possible' (Porter and Serra, 2020).

At baseline, a random one-half of the sample was shown the documentary followed by a brief discussion to reiterate the key messages of the documentary. The main message of the documentary was reinforced in a follow-up survey four months later as well. We collected high-frequency data by conducting three further follow-up surveys to track students' job search e ort and incidence of working. Apart from showing a 10-minute video, the entire sample was also given information regarding a job matching service 'Job Asaan' to alleviate the information constraints.

Our results show that immediately after showing the video treated individuals show a higher growth mindset while also scoring higher on the absorption index. Also

18 months after being treated individuals have a 4.7% higher chance of working. Although a lot of them are working as tutors. This finding also nicely ties in with our conjecture in the second chapter that women tend to enter either the education or health sector for jobs.

What is also interesting about our results is that a heterogeneity analysis reveals that students who come from relatively worse-off households have a higher chance of working 18 months after the baseline compared to those who come from a better-off household. The entire effect at the endline is entirely driven by this sub-sample of students. We find no impact of the intervention at any point on the job-search efforts or work status of the students except at 18 months and this could be because most students end up working as home-based tutors after they graduate which does not require one to actively search for jobs.

The results of each of these chapters have important policy implications. The findings of the chapter on gender wage decomposition highlight that since women tend to concentrate on a handful of jobs, there is a need to make other jobs inclusive too by creating other gender-friendly job opportunities that women may find feasible to join given their preferences eg. maintaining work-life balance, temporal flexibility etc. These findings could also be indicating a general lack of information or misinformation regarding jobs in the other sectors. Because households are not well aware of other job opportunities they prefer jobs and sectors that they have greater information about from their peers or general social circle. The policy in this regard in addition to making more gender-friendly jobs available should also focus on removing the information barrier between the demand and supply side of the labour market for instance by investing in job matching services that provide accurate information not only to employers about the competencies and skills of the available pool of candidates but also provide job seekers information regarding potential job opportunities that suit their preferences.

The chapter on returns to tertiary education shows the importance of investing in physical infrastructure to spur investment in human capital. Expanding the supply of tertiary education institutes increases investment by households in higher education as it allows easier access to affordable opportunities. What is further interesting about these results is that the significance is entirely driven by the lagging regions where there is a paucity of opportunities. The other major finding from this chapter was how marginal returns for an extra year of education beyond matriculation are a source of relatively higher extra returns for women than for men. This could be because the gender wage gap is inversely related to years of schooling especially the unexplained part attributed to ’discrimination, tastes and circumstances (DTC)’ (Dougherty, 2005). This is probably because more educated women have a degree or formal qualification that lands her in a job that makes standardized wage offers or a better-educated woman may be able to deal well with discrimination or may even be able to find better job openings for herself where her characteristics are rewarded fairly (Dougherty, 2005). This finding ties in well with what we find in chapter 2 that as one moves above the wage distribution gender wage gap tends to fall and that at the bottom of the wage distribution gender wage gap is largely caused by the unexplained gap which tends to shrink as one moves up the distribution. An important implication for policy here of course is to invest resources into improving the human capital of women as this tends to reduce the wage gap by the direct effect of human capital itself and an indirect effect of dampening the DTC effect.

Also, an added benefit of investing in tertiary education institutions in the less developed regions is the growth of private low-cost high schools in the area, which in turn could increase the number of primary schools in the area, i.e. improve across-the-board increase in the level of education in the region potentially by increasing the supply of school teachers graduating from these tertiary education institutes (Andrabi et al., 2008).

Chapter 4 reveals that soft touch interventions are not enough of a push to affect life-changing outcomes such as a decision to enter labour force. We see a significant impact of a motivational nudge on the psychological state of individuals by showing a higher growth mindset but only immediately after the interventions were rolled out. There is evidence of treated individuals working months after the light-touch nudge but that also is possible due to the timing of the endline coinciding with the start of the nationwide lockdown. Our results additionally show that treated students who belong to low-income households tend to have been affected much more than those coming from well-off households but this could have been driven by the high levels of stress reported by these girls during lockdown for a fear of job loss of income loss. Overall the results show that for approaching the problem of low female labour force participation by relying on such unconventional means where exposing potential job market entrants to relatable role models may help by affecting short-term outcomes but in the long run, the effect fades away.

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Appendices

2.1 Appendix A1

Year	2006		2014	
	Contribution of Explanatory Variables to Gender Gap		Contribution of Explanatory Variables to Gender Gap	
Variable	**Coefficients**	**Percentage of Gap**	**Coefficients**	**Percentage of Gap**
Panel A: Base Specification				
Education	0.108	16%	0.139	16%
Experience	-0.011	-2%	0.156	18%
Married	0.000	0%	-0.118	-14%
Region	0.071	10%	0.049	6%
Explained Gap	0.163	23%	0.221	25%
Unexplained Gap	0.531	77%	0.647	75%
Total Wage Gap	0.694	100%	0.868	100%
Panel B: Full Specification				
Education	-0.153	-23%	-0.398	-46%
Experience	0.066	10%	0.231	26%
Married	0.028	4%	-0.039	-4%
Gender ratio: Professions	0.060	9%	0.093	11%
Gender ratio: Industry	0.044	7%	-0.219	-25%
Region	0.071	10%	0.061	7%
Industry	0.050	7%	0.158	18%
Profession	0.155	22%	0.161	18%
Explained Gap	0.240	36%	0.048	5%
Unexplained Gap	0.428	64%	0.828	95%
Total Wage Gap	0.668	100%	0.876	100%

Note: This table shows the decomposition of the gender wage gap into explained and unexplained parts correcting for selection bias using Oaxaca Blinder Methodology with Heckman's two-step procedure for the years 2006 and 2014 using PSLM. The selection bias due to selection into paid work is corrected for using the household's possession of assets (Asadullah, 2019)) such as agricultural land, commercial building, poultry, livestock, residential building, and animal transport as the exclusion restriction. The selection into higher education is corrected for using 'parental education'. As parental education was available for a very small number of individuals the results are not comparable to the rest of the tables.

2.2 Appendix A2

Table A21: Selection functions for the wage decomposition analysis in Table 6 (Model 1)

	(1)	(2)	(3)	(4)	(5)	(6)	(5)	(6)
	Base 2006		Base 2014		Full 2006		Full 2014	
LABELS	select	mills	select	mills	select	mills	select	mills
Years of education	-18.29		-0.26		-56.37		39.06	
	(650.49)		(1.66)		(3,763.88)		(2,127.28)	
Years of education squared	0.68		0.02		1.78		-0.89	
	(25.02)		(0.06)		(170.28)		(149.34)	
Years of experience	0.01		0.05		-5.13		-1.59	
	(0.12)		(0.08)		(976.80)		(729.44)	
Experience squared	-0.00		-0.00		0.13		0.01	
	(0.00)		(0.00)		(11.13)		(14.11)	
Marital status	2.07*		0.38		45.85		63.65	
	(1.22)		(0.61)		(0.00)		(0.00)	
Gender ratio: Prof					-21.63		-46.03	
					(0.00)		(0.00)	
Gender ratio: Ind					-27.94		85.34	
					(0.00)		(0.00)	
Total children in the hh under the age of 7	-0.30		0.08		-10.03		-12.32	
	(0.21)		(0.15)		(1,520.76)		(678.09)	
HH owns Agr. land	0.23		0.28		20.35		60.88	
	(0.68)		(0.47)		(7,024.10)		(0.00)	
HH owns Livestock	-8.03		-0.01		-39.02		-57.88	
	(1,066.88)		(0.57)		(6,779.23)		(0.00)	
HH owns sheep/goat	-1.87		-4.93		5.21		-90.35	
	(1,066.88)		(1,519.21)		(0.00)		(0.00)	
HH owns poultry	-2.86		-4.89		27.08		-24.67	
	(1,066.88)		(1,519.21)		(0.00)		(0.00)	
HH owns commercial building	-4.45		0.10		-21.01		16.11	
	(1,055.61)		(0.59)		(0.00)		(0.00)	
HH owns Animal transport	-1.91		0.00		-23.25		0.55	
	(1,066.88)		(0.66)		(6,996.28)		(0.00)	
lambda		-0.42		-2.33		-3736214.85		-22203668.12

		(0.46)		(2.59)		(3.65e+13)		(8.20e+14)
Districts	Y		Y		Y		Y	
Industry variables	N		N		Y		Y	
Profession variables	N		N		Y		Y	
Constant	167.51		25.67		657.72		-33.87	
	(0.00)		(0.00)		(0.00)		(0.00)	
Observations	2,925	2,925	2,487	2,487	2,539	2,539	2,417	2,417

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A22: Selection functions for Heckman Selection done for correcting for selection into higher education for wage decomposition analysis shown in Table 7 (Model 2a)

	(1)	(2)	(3)	(4)
	Year 2006		Year 2014	
VARIABLES	select	mills	select	mills
Years of experience	-0.10***		-0.12***	
	(0.01)		(0.01)	
Experience squared	0.00***		0.00***	
	(0.00)		(0.00)	
Marital status	0.83***		0.89***	
	(0.07)		(0.07)	
Avg. education of the hh (excluding self)	0.16***		0.15***	
	(0.01)		(0.01)	
Lambda		-27.10***		-15.12***
		(6.97)		(2.99)
Districts	Y		Y	
Constant	3.42***		2.51***	
	(0.25)		(0.14)	
Observations	67,724	67,724	70,415	70,415

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A23: Selection functions for the wage decomposition analysis in Table 7 (Model 2a)

	(2)	(3)	(5)	(6)	(8)	(9)	(11)	(12)
	Base 2006		Base 2014		Full 2006		Full 2014	
VARIABLES	select	mills	select	mills	select	mills	select	mills
Years of education			-0.26		-52.80		4.04***	
			(1.66)		(18,061.85)		(0.28)	
Years of education squared	-0.01		0.02		1.60		-0.14***	
	(0.01)		(0.06)		(1,141.66)		(0.01)	
Years of experience	0.06		0.05		-5.57		0.06***	
	(0.09)		(0.08)		(777.76)		(0.02)	
Experience squared	-0.00		-0.00		0.14		-0.00*	
	(0.00)		(0.00)		(24.90)		(0.00)	
Marital status	1.69*		0.38		47.90		0.26**	
	(0.87)		(0.61)		(11,653.46)		(0.11)	
Gender ratio: Prof					-24.64		-0.31	
					(0.00)		(0.43)	
Gender ratio: Ind					-37.22		-0.87	
					(0.00)		(0.72)	
Total children in the hh under the age of 7	-0.30		0.08		-10.11		-0.11***	
	(0.19)		(0.15)		(1,608.05)		(0.03)	
HH owns Agr. land	0.26		0.28		22.75		0.10	
	(0.61)		(0.47)		(20,033.62)		(0.11)	
HH owns Livestock	-8.70		-0.01		-45.02		-0.18	
	(1,021.23)		(0.57)		(10,325.09)		(0.14)	
HH owns sheep/goat	-2.83		-4.93		4.74		-0.13	
	(1,279.49)		(1,519.21)		(0.00)		(0.19)	
HH owns poultry	-3.98		-4.89		26.58		0.12	
	(1,567.11)		(1,519.21)		(0.00)		(0.18)	
HH owns commercial building	-4.34		0.10		-18.87		0.82***	
	(1,758.75)		(0.59)		(16,908.93)		(0.13)	
HH owns Animal transport	-3.02		0.00		-24.43		0.09	
	(980.30)		(0.66)		(0.00)		(0.15)	

lambda		-0.45		-2.29		14102965.07		-0.04
Districts	Y		Y		Y		Y	
Industry variables	N		N		Y		Y	
Profession variables	N		N		Y		Y	
Constant	52.80		25.67		654.97		-17.60	
	(0.00)		(0.00)		(0.00)		(0.00)	
Observations	2,925	2,925	2,487	2,487	2,539	2,539	7,329	7,329

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

2.2 Appendix A3

Other Decomposition Techniques

a) Unconditional Quantile Regression Estimator

Machado and Mata (2005) have used quantile regression-based estimators to estimate the counterfactual unconditional wage distributions. The unconditional quantile estimator is not the same as the conditional quantile estimator in that it relies on generating a random sample from the covariates' distribution and then determining the distribution of the outcome variable using coefficients from the conditional quantile regression at randomly sampled quantiles. The counterfactual distribution, in the same way, is determined by drawing a random sample of covariates from a different distribution (e.g. women's) and using a coefficient from a different distribution (e.g. men's). To estimate the counterfactual wage distribution for instance this technique would use a randomly generated sample of size m of covariates from the rows of the vector of women's characteristics $(X^*_{Wi}), i = 1 \ldots m$ and the coefficient vector $(\hat{\beta}_M)$generated in the m different conditional quantile regressions $Q_{u_i}(y|X_M)$used to estimate the wages of men using their characteristics at randomly determined quantiles (u_i).

The unconditional wage distribution for men using this technique is given as follows:

$\boldsymbol{y^*_M = X^*_{Mi}\widehat{\beta}_M(u_i)}$ **.....2. 4**

And the counterfactual wage distribution i.e. the men's wage distribution if they had the characteristics of women but continued to be paid like men in the labour market is given as follows:

$$\boldsymbol{y_{M_i}^{C^*} = X_{Wi}^* \widehat{\beta}_M(u_i)} \text{ .....2. 5}$$

The decomposition of the wage gap in this method into the endowments and coefficients effect at a given quantile θ can be represented as

$$\boldsymbol{(y_M - y_W)_\theta = (Q_\theta(y_M^* | X_M^*) - Q_\theta(y_M^{C^*} | X_W^*)) - (Q_\theta(y_M^{C^*} | X_W^*) - Q_\theta(y_W^* | X_W))} \text{ .....2. 6}$$

This estimator has been used extensively in the literature in various contexts such as estimating racial earnings differences (Bayer and Charles, 2018), housing expenditures and income inequality (Dustmann et al, 2018), migrants and local urban residents' earnings gap (Ma, 2018) or union and non-union workers' earnings differential (Biewen and Seckler, 2019).

b) Distribution regression estimator

Chernozhukov, Fernandez-Val, and Melly (2013) have introduced distribution regression for modeling and estimating counterfactual distribution. The conditional distribution, that this method estimates, comes from performing inference about the effect of a change in either the distribution of independent variables or the relationship of the outcome variable with these independent variables on an outcome variable. The counterfactual distribution is estimated by estimating the distribution function of wages of the reference group had they faced the other group's wage schedule given their characteristics. In our case the counterfactual distribution is estimated by integrating the conditional distribution of men's wages with respect to the distribution of women's characteristics as follows:

$$\boldsymbol{F_{Y(M|W)}(y) := \int_{X_W} F_{Y_M|X_M}(y|x) dFX_W(x)} \text{ .....2. 7}$$

Where M stands for men and W for women and $F_{Y(i|i)}$ represents the observed wages distribution of men and women and y is the outcome varia)ble and x denotes the set of covariates. $F_{Y(M|W)}$ denotes the counterfactual distribution function of women's wages had they faced men's wage schedule. This counterfactual distribution is then decomposed using the Oaxaca blinder procedure as follows:

$$\boldsymbol{F_{Y(M|M)} - F_{Y(W|W)} = \left(F_{Y(W|W)} - F_{Y(M|W)} \right) - (F_{Y(M|W)} - F_{Y(M|M)})} \text{ .....2. 8}$$

Whereas on the left-hand side the first bracket represents the wage that is due to the wage structure effect or pure discrimination and the second bracket reflects the wage gap due to characteristics or endowments.

This estimator has been used in a variety of settings for estimating the gender wage gap for instance for the United Kingdome (Bryson et al, 2022), the United States (Fernandez et al, 2018), Lebanon (Harb et al, 2020) or Vietnam (Vu and Yamada, 2018).

c) Recentered Influence Function Regressions

A recently developed unconditional quantile estimation technique based on Firpo et al. (2009) allows consists of running a regression of a transformation of the outcome variable the Recentered Influence Function (RIF) on the explanatory variables. It involves creating a counterfactual distribution of the outcome variable by computing a reweighting factor. The counterfactual wage distribution is obtained for the control group, females in our case, by "reweighting" the observations for males in such a way that the sample of males resembles the sample of females in terms of the observable characteristics where the reweighting factor is computed as follows:

$$\boldsymbol{\varphi(x_i) = \frac{\left((1 - Pr(male|x_i)) * Pr(male)\right)}{((Pr(male|x_i)) * (1 - Pr(male))}} \text{ .....2. 9}$$

In this expression $\Pr(male)$ is the proportion of males in the sample and $\Pr(male|x_i)$ is the probability of being a working male given the observable characteristics and is obtained as fitted values from a probit regression of gender on observable characteristics.

The total wage gap then is decomposed as follows:

$$\hat{\boldsymbol{y}}_{\boldsymbol{m}} - \hat{\boldsymbol{y}}_{\boldsymbol{f}} = (\hat{\boldsymbol{y}}_{\boldsymbol{m}} - \hat{\boldsymbol{y}}_{\boldsymbol{c}}) + (\hat{\boldsymbol{y}}_{\boldsymbol{c}} - \hat{\boldsymbol{y}}_{\boldsymbol{f}}) \quad \textbf{.....2. 10}$$

The “explained” part of the decomposition is called the ‘composition effect’ $(\hat{y}_m - \hat{y}_c)$ since it reflects differences in the distribution of the X’s between the two groups and the “unexplained” part of the decomposition is called the wage “structure effect” $(\hat{y}_c - \hat{y}_f)$ as it reflects differences in the β’s, i.e. in the way the X’s are “priced” (or valued) in the labour market. The composition effect $(\hat{y}_m - \hat{y}_c)$ reflects differences in the distribution of the X’s between the two groups

$$(\hat{\boldsymbol{y}}_{\boldsymbol{m}} - \hat{\boldsymbol{y}}_{\boldsymbol{c}}) = (\overline{\boldsymbol{x}}_{\boldsymbol{m}} - \overline{\boldsymbol{x}}_{\boldsymbol{c}})'\hat{\boldsymbol{\beta}}_{\boldsymbol{m}} + \overline{\boldsymbol{x}}_{\boldsymbol{ck}}(\hat{\boldsymbol{\beta}}_{\boldsymbol{m}} - \hat{\boldsymbol{\beta}}_{\boldsymbol{c}}) \quad \textbf{.....2. 11}$$

Where the second term is the specification error, if the actual wage process is truly linear then this error should converge to zero. The wage structure effect reflects differences in the β’s, i.e. in the way the X’s are “priced” (or valued) in the labour market

$$(\hat{\boldsymbol{y}}_{\boldsymbol{c}} - \hat{\boldsymbol{y}}_{\boldsymbol{f}}) = \overline{\boldsymbol{x}}'_{\boldsymbol{f}}(\hat{\boldsymbol{\beta}}_{\boldsymbol{c}} - \hat{\boldsymbol{\beta}}_{\boldsymbol{f}}) + (\overline{\boldsymbol{x}}_{\boldsymbol{c}} - \overline{\boldsymbol{x}}_{\boldsymbol{f}})'\hat{\boldsymbol{\beta}}_{\boldsymbol{c}} \quad \textbf{.....2. 12}$$

Where the second term is the reweighting error, if the reweighting term has been constructed correctly then this term should converge to zero. If both the specification and the reweighting error terms converge to zero then this decomposition converts to OB decomposition.

This estimator has been used in various contexts such as for estimating the rural-urban learning achievements gap (Sanfo and Ogawa, 2021), or the gender wage gap in developing countries (Si et al, 2021) or to estimate inequalities in the health insurance coverage (Renna et al, 2021).

To the best of our knowledge, no study in Pakistan employs three methods together to compute the wage gap

Robustness Checks

To further explore these results to see the trend in the gender wage gap and its two components for each year independently across the entire wage distribution this analysis employs three other decomposition techniques as tests of robustness. These techniques as described earlier in section 4 differ based on the construction of the counterfactual distribution. The results of each of these decomposition techniques for the full specification have been discussed below.

Unconditional Quantile Regression Estimator

As discussed earlier this decomposition technique disaggregates the gender gap into an endowment and a coefficient effect but that according to equation 12 requires the construction of a counterfactual group by the method of random sampling as explained already. The results of the unconditional quantile regression estimator as proposed by Machado & Mata (2005) are shown in figure 10 below. The figure reports quantile-wise results for each of the two years separately. One can see that both in the years 2006 and 2014 the trend in the wage gap down from the bottom of the wage distribution to the top of the wage distribution has roughly stayed the same. The results here also show that for both the years there is a substantial gender gap at all parts of the distribution and the coefficient effect has been the major contributing factor to this gender gap. The coefficients effect or gender discrimination is largest at the bottom end of the distribution and it falls as one moves towards the top of the distribution, the ‘sticky floor’ effect. The characteristics or the endowments effect on the other hand seems to be contributing uniformly across all quantiles making gender discrimination the defining factor for the trend followed by the total gender gap. Another important thing to note here is that as one moves to the top of the distribution the coefficients effect converges with the endowments effect showing that endowments and the coefficient effect contribute equally to the gender wage gap at the top. All of these results conform to our earlier findings with the Oaxaca decomposition analysis in section 7.

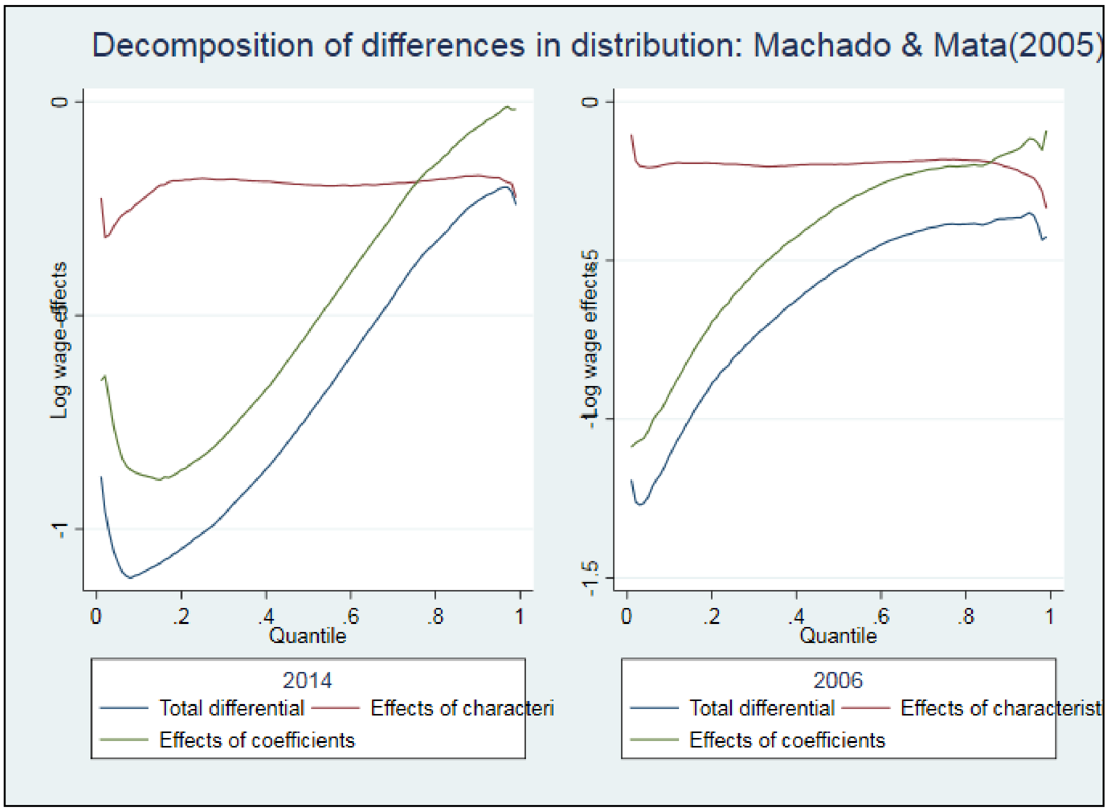

Figure 2. 10 Decomposition of Differences in Distribution for Men and Women Using Unconditional Quantile Regression: Machado & Mata Decomposition (2005)

Recentered Influence Function Regressions

This technique decomposes the gender gap into the endowments and coefficients effect by estimating the counterfactual densities using propensity scores known as the reweighting factors described in section 3 earlier. The results from this technique are shown in figure 11. The figure again shows the decomposition of the total wage gap into an endowment effect and a coefficient effect for both the years of our analysis. The results from this technique too yield similar results as from the earlier decomposition techniques. The curves however are kinky rather than being smooth as the decomposition is done in this technique for a given quantile and not at all parts of the distribution. Looking at the figure one notices again that the total wage gap is substantial throughout the distribution and the deciding factor again according to this decomposition has been the coefficients effect. The phenomenon of sticky floors is evident from this technique as well.

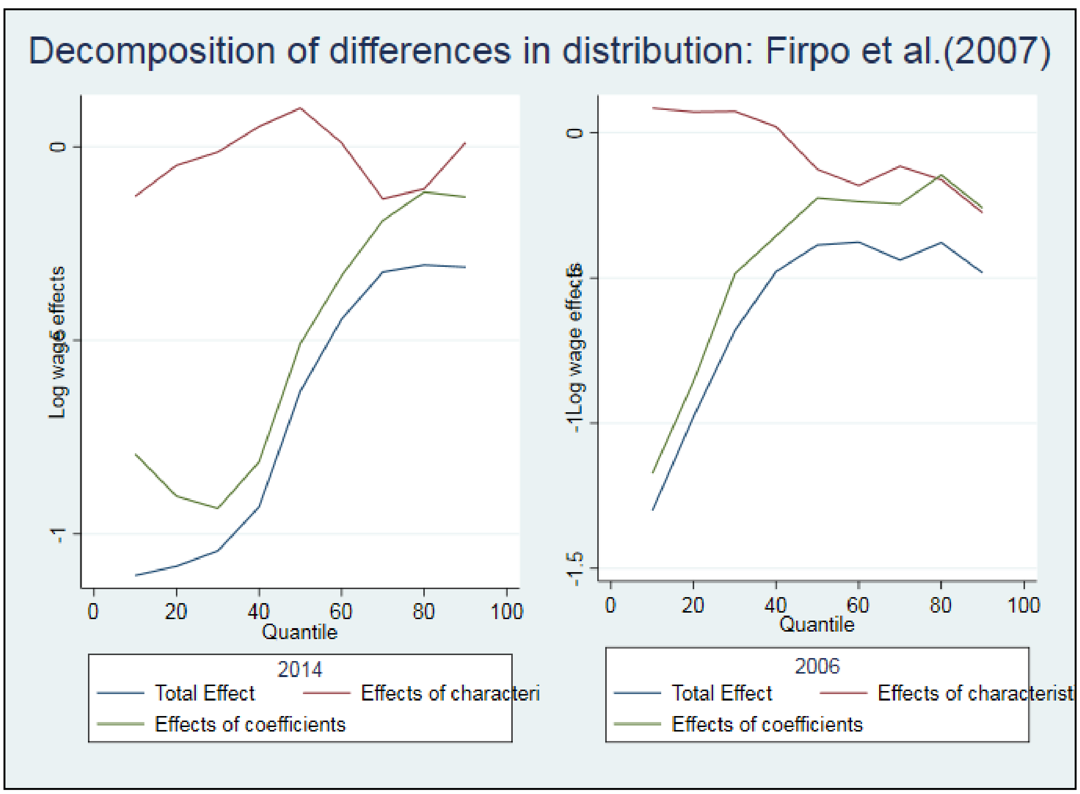

Figure 2. 11 Decomposition of Differences in Distribution for Men and Women Using RIF Regression: Firpo et al (2009)

Distribution regression estimator

Our results from the last estimator are also somewhat similar in that the coefficient gap is highest at the bottom and lowest at the top. The endowment effect seems to matter roughly equally at all parts of the distribution. The total wage gap is highest at the bottom of the distribution. What is, however, different from earlier results is that the coefficient effect crosses the endowment effect at the middle of the distribution. The endowments line and the coefficients line intersect in both years somewhere around the middle of the distribution suggesting that the endowment effect matters much more than the coefficient effect starting from the middle of the distribution (figure 12). The intersection makes the endowments effect more important in determining the value of the total gap for the remaining part of the distribution once the two curves cross. It is not to say that gender discrimination does not play a part in determining the total wage gap but that the characteristics matter more on the top of the wage distribution.

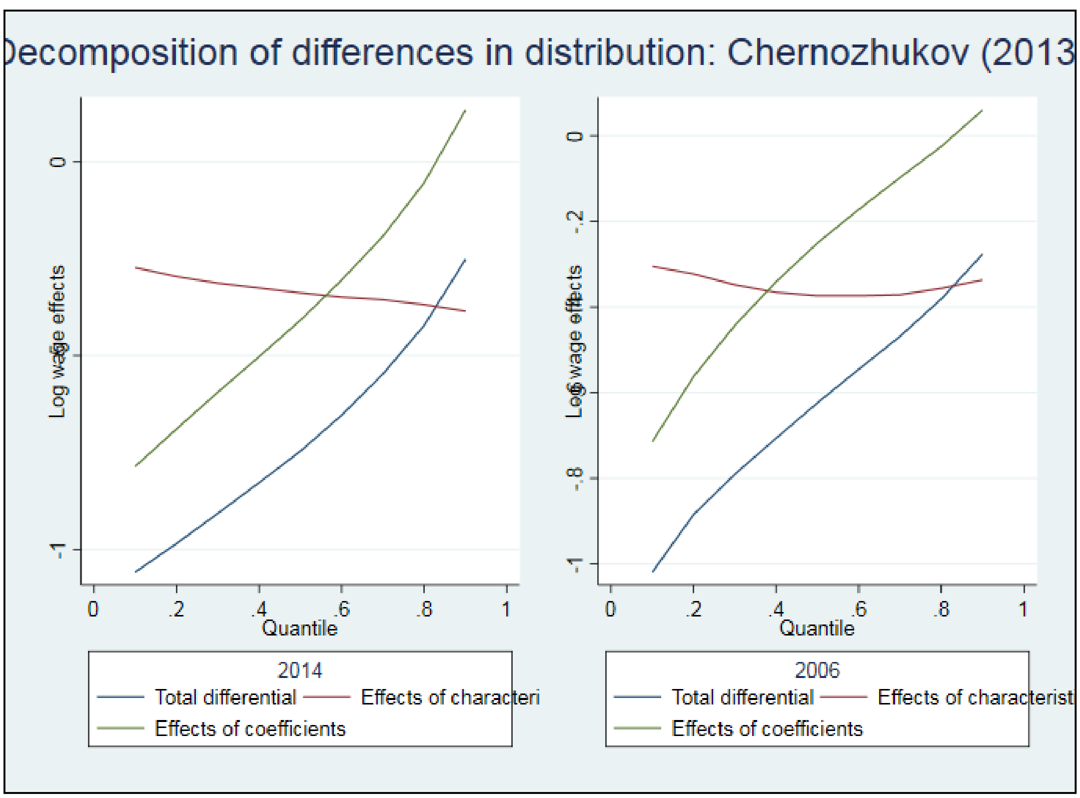

Figure 2. 12 Decomposition of Differences in Distribution for Men and Women Using Distribution Regression Estimator: Chernozhukov, Fernandez-Val, and Melly (2013)

2.3 Appendix B1

Table B11: Decomposition of gender wage gap adjusted for selection and endogeneity bias (IV: Gender composition of the household) (Model 2d)

Year	**2006**		**2014**	
	Contribution of Explanatory Variables to Gender Gap		Contribution of Explanatory Variables to Gender Gap	
Variable	**Coefficients**	**Percentage of Gap**	**Coefficients**	**Percentage of Gap**
Panel A: Base Specification				
Education	0.000	0%	0.000	0%
Experience	0.119	19%	0.177	25%
Married	0.049	8%	0.019	3%
Region	0.045	7%	0.019	3%
Explained Gap	0.213	33%	0.215	31%
Unexplained Gap	0.424	67%	0.481	69%
Total Wage Gap	0.637	100%	0.696	100%
Panel B: Full Specification				
Education	0.000	0%	0.000	0%
Experience	0.109	18%	0.156	23%
Married	0.035	6%	0.019	3%
Gender ratio: Professions	0.012	2%	-0.038	-6%
Gender ratio: Industry	-0.017	-3%	0.025	4%
Region	0.031	5%	0.019	3%
Industry	-0.002	0%	0.003	0%
Profession	-0.013	-2%	-0.038	-5%
Explained Gap	0.156	25%	0.146	21%
Unexplained Gap	0.456	75%	0.544	79%
Total Wage Gap	0.611	100%	0.690	100%

Note: This table shows the decomposition of the gender wage gap into explained and unexplained parts correcting for selection bias using Oaxaca Blinder Methodology with Heckman's two-step procedure for the years 2006 and 2014 using PSLM. The selection bias due to selection into paid work is corrected for using the household's possession of assets (Asadullah, 2019)) such as agricultural land, commercial building, poultry, livestock, residential building, and animal transport as the exclusion restriction. The endogeneity due to sample selection and omitted variables is corrected for using gender composition of the household as IV. The gender composition consists of the number of female and male individuals controlled for separately in the first stage of IV regression. The results for the first stage of IV regressions of all specifications are available on request. The F-stat of the first stage of base specification for 2006 is 0.86 and for 2014 it is 0 .22. The F-stat of the first stage of full specification for 2014 is 0.47 and for 2014 it is 0.06.

Table B12: First stage regression for Table 8 and Table 9 (Model 2b and 2c)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Dependent Variable: Years of Education							
Avg. education of the hh (excluding self)	-0.04	-0.04	0.08***	0.05*				
	(0.03)	(0.03)	(0.03)	(0.03)				
Avg. education of the hh (excluding self) sq.	0.01***	0.01***	0.00	0.00				
	(0.00)	(0.00)	(0.00)	(0.00)				
Education of the hhead					-0.97***	-0.89***	-0.96***	-0.92***
					(0.05)	(0.05)	(0.05)	(0.05)
Education of the hhead sq.					0.05***	0.05***	0.05***	0.05***
					(0.00)	(0.00)	(0.00)	(0.00)
Years of experience	-0.07***	-0.08***	0.02*	0.01	-0.10***	-0.10***	-0.03***	-0.03***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Experience squared	0.00***	0.00***	-0.00***	-0.00***	0.00***	0.00***	0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Gender ratio: Prof	0.56***	0.13	0.49***	-0.03	0.45***	0.13	0.41***	0.01
	(0.10)	(0.13)	(0.05)	(0.07)	(0.08)	(0.11)	(0.04)	(0.06)
Gender ratio: Ind	0.66***	-0.09	0.53***	-0.16	0.39***	0.09	0.35***	-0.19
	(0.14)	(0.22)	(0.09)	(0.17)	(0.12)	(0.19)	(0.08)	(0.15)
Marital status	0.82***	0.71***	0.63***	0.62***	0.13*	0.12*	0.11	0.16**
	(0.08)	(0.08)	(0.08)	(0.08)	(0.07)	(0.07)	(0.08)	(0.07)
Districts	Y	Y	Y	Y	Y	Y	Y	Y
Industry variables	N	y	N	y	N	y	N	y
Profession variables	N	Y	N	Y	N	Y	N	Y
F-stat of first stage	107.71	77.56	56.38	33.93	831.85	693.89	598.42	546.78
Observations	3,173	3,173	3,259	3,259	2,876	2,876	2,933	2,933

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

4.1 Appendix 4.1

A Additional figures and tables

Figure A1: Location of Women only Public Colleges in Lahore

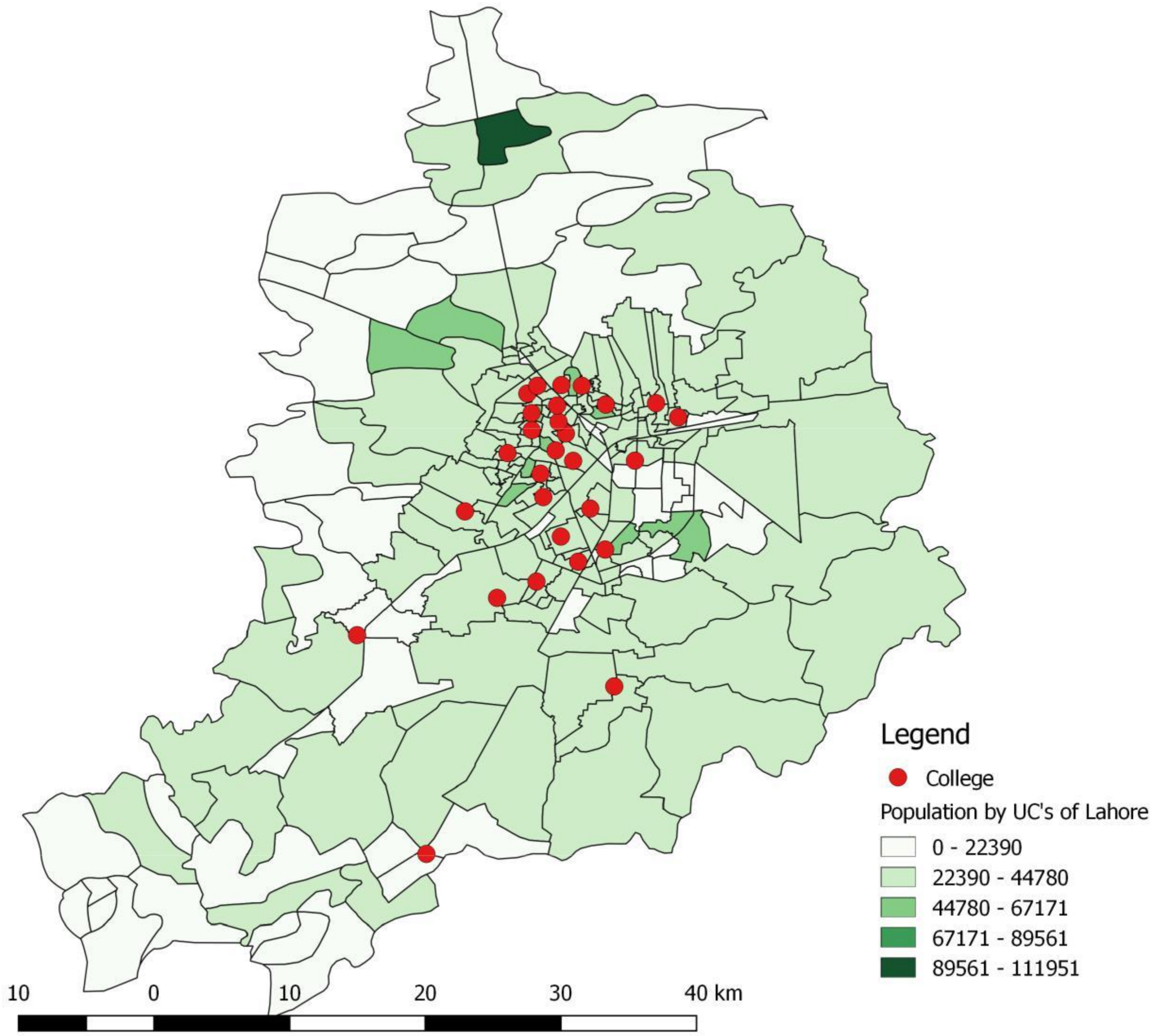

Table A.1: Attrition by survey round, including baseline characteristics

	(1)	(2)	(3)	(4)
Months since baseline	3	9	12	18
Treated	0.112	0.091	0.174	0.097
	(0.078)	(0.084)	(0.114)	(0.116)
Monthly household income (USD)	0.000	0.000*	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Dummy: Own house	0.067***	0.023	0.033	0.100***
	(0.020)	(0.025)	(0.036)	(0.035)
Household size	-0.006	0.001	-0.006	-0.006
	(0.005)	(0.006)	(0.007)	(0.008)
Father's years of education	0.002	-0.002	0.006**	0.001
	(0.002)	(0.002)	(0.003)	(0.003)
Mother's years of education	-0.002	0.001	-0.004	-0.002
	(0.002)	(0.002)	(0.003)	(0.003)
Dummy: Mother works	-0.025	-0.091***	0.014	-0.068
	(0.031)	(0.026)	(0.049)	(0.048)
Dummy: Want to work after graduation	-0.005	0.008	0.002	0.027
	(0.028)	(0.030)	(0.040)	(0.041)
Dummy: Married	0.003	0.007	-0.028	-0.020
	(0.036)	(0.036)	(0.047)	(0.052)
Hours of study per day	0.000	0.002	0.004	-0.002
	(0.005)	(0.005)	(0.006)	(0.006)
Hours of housework	0.003	0.006	0.006	0.013*
	(0.007)	(0.007)	(0.008)	(0.008)
Dummy: searched for a job	-0.075**	-0.030	-0.083	-0.021

	(0.03)	(0.04)	(0.07)	(0.07)
Hours of job search in the last 4 months	-0.002	0	0.009	-0.005
	(0.00)	(0.01)	(0.01)	(0.01)
Monthly personal income (USD)	0	0	0	0
	(0.00)	(0.01)	(0.01)	(0.01)
Monthly household income (USD) *T	0	0	0	0
	(0.00)	(0.00)	(0.00)	(0.00)
Dummy: Own house *T	-0.046	0.017	0.006	-0.021
	(0.03)	(0.03)	(0.05)	(0.05)
Household size *T	-0.003	0.001	0.002	-0.002
	(0.01)	(0.01)	(0.01)	(0.01)
Father’s years of education *T	0.002	0.002	-0.008*	0.002
	(0.00)	(0.00)	(0.00)	(0.00)
Mother’s years of education *T	0	0	0	-0.003
	(0.00)	(0.00)	(0.00)	(0.01)
Dummy: Mother works *T	0.064	0.166***	0.027	0.153**
	(0.05)	(0.05)	(0.07)	(0.08)
Dummy: Want to work after graduation *T	-0.021	-0.062	-0.063	-0.058
	(0.04)	(0.04)	(0.06)	(0.06)
Dummy: Married *T	0.06	0.025	0.05	0.138*
	(0.05)	(0.05)	(0.07)	(0.07)
Hours of study per day *T	-0.002	-0.01	-0.01	-0.001
	(0.01)	(0.01)	(0.01)	(0.01)
Hours of housework per day *T	-0.007	-0.006	-0.003	0
	(0.01)	(0.01)	(0.01)	(0.01)
Dummy: searched for a job *T	0.085	-0.018	0.01	-0.108
	(0.08)	(0.08)	(0.11)	(0.11)
Hours of job search in the last 4 months *T	0.011	0.008	0.006	0.025**
	(0.011)	(0.013)	(0.015)	(0.012)
Monthly personal income (USD) *T	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.091*	0.053	0.246***	0.246***
	(0.054)	(0.057)	(0.079)	(0.083)
p(F-stat)	0.13	0.09	0.70	0.30
Mean	0.13	0.12	0.30	0.35
Observations	2183	2183	2183	2183

Note: Column (1) reports attrition from the intervention reinforcement survey (3 months after the baseline), column (2) from follow-up 1 (9 months after the baseline), column (3) from follow-up 2 (12 months after the baseline), and column (4) from follow-up 3 (18 months after the baseline). All results are from a saturated regression with controls for household characteristics (monthly household income, dummy for own house, household size, father's yeas of education, mother's years of education, and dummy for mother works) and respondents' own characteristics (dummies for if wants to work after graduation, and is married, hours of study and housework per day, dummy for if searched for job, hours of job search in the last 4 months, and monthly personal income) and the interaction of these controls with the treatment dummy ('T'). All covariates are collected before the intervention is implemented. Observations are lower due to missing observations in baseline characteristics. Robust standard errors are presented in parentheses. 'p(F-stat)' refers to the p-value of F-Statistic from a test of joint significance of the interaction of treatment status and baseline characteristics. 'Mean' refers to the average level of attrition in each round. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.2: Effect on job search and work status over time

Dependent variable:	Job search				Work status			
Time after intervention:	9 months	12 months	15 months	18 months	9 months	12 months	15 months	18 months
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treated	0.020	-0.013	-0.003	-0.002	-0.003	0.011	0.0200	0.047**
	(0.015)	(0.016)	(0.016)	(0.010)	(0.019)	(0.022)	(0.024)	(0.021)
MDE	0.042	0.0448	0.0448	0.028	0.053	0.062	0.067	0.059
Lower bound	0.015	-0.018	-0.004	-0.003	-0.008	0.008	0.015	0.045
	(0.017)	(0.018)	(0.015)	(0.011)	(0.019)	(0.024)	(0.023)	(0.017)***
Upper bound	0.023	-0.006	0.000	0.001	-0.000	0.020	0.019	0.049
	(0.018)	(0.023)	(0.023)	(0.016)	(0.021)	(0.025)	(0.030)	(0.025)**
Observations	2189	1746	1614	1614	2186	1744	1614	1614
Mean (placebo)	0.171	0.154	0.128	0.0461	0.290	0.277	0.338	0.201

Note: This table displays results from an OLS regression testing treatment effects on job search efforts and work status. The dependent variable in columns (1) to (4) is a binary variable equal to 1 if the respondent looked for work in the last month. The dependent variable in columns (5) to (8) is a binary variable equal to 1 if the respondent is working at the time of the survey. 'Treated' is a binary variable equal to one for respondents who viewed the role model video; 0 for those who viewed the placebo videos. The lower and upper bounds refer to the treatment effect bounds constructed using the Lee (2009) procedure. 'MDE' refers to ex post minimum detectable effect size at a significance level of 0.05 and power of 80 percent.'Mean placebo)' is the average value of the dependent variable for the placebo group. Robust standard errors are presented in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.3: Effect on job search index components (conditional on searching)

Time after intervention	9 months	12 months	15 months	18 months
	(1)	(2)	(3)	(4)
Panel (a): Job search hours				
Treated	-0.0509	0.736	2.564	7.700
	(1.084)	(0.859)	(3.709)	(11.91)
Observations	393	255	205	72
Mean (placebo)	10.04	7.130	7.623	10.29
Panel (b): Read job ads				
Treated	-0.0320	0.0772	-0.0969	-0.0355
	(0.0438)	(0.0652)	(0.0715)	(0.152)
Observations	393	255	205	72
Mean (placebo)	0.229	0.406	0.425	0.395
Panel (c): Search via informal networks				
Treated	-0.00696	0.0853	0.0658	0.0382
	(0.0428)	(0.0518)	(0.0600)	(0.153)
Observations	393	255	205	72
Mean (placebo)	0.802	0.783	0.764	0.684
Panel (d): Online job search				
Treated	0.00332	-0.0264	-0.0246	0.0194
	(0.0484)	(0.0651)	(0.0726)	(0.128)
Observations	393	255	205	72
Mean (placebo)	0.531	0.587	0.575	0.763
Panel (e): Formal job search				
Treated	0.0124	-0.00387	-0.0750	-0.0538
	(0.0525)	(0.0646)	(0.0729)	(0.148)
Observations	393	255	205	72
Mean (placebo)	0.469	0.493	0.575	0.316

Note: This table displays results from an OLS regression testing treatment effects on job search efforts on sample of students who appear in each round and report having looked for a job in the last 4 weeks. The dependent variable in panel (a) is the approximate number of hours they spent on job search during the last 4 weeks, the dependent variables in panels (b) - (e) are binary variables for different activities the respondents undertook to look for a job where ‘Read job ads’ is a binary indicator variable for respondents who have read job advertisements while looking for a job over the past 4 weeks. ‘Search via informal networks’ is an indicator variable for respondents who have asked family members, friends, colleagues etc. for a job, ‘Online job search’ is an indicator variable for respondents who have searched for or responded to job advertisements online while looking for a job over the past 4 weeks, ‘Formal job search’ is an indicator variable for respondents who have contacted potential employers, temporary employment agencies or the public employment service while searching for a job over the past 4 weeks. ‘Treated’ is a binary variable equal to one for respondents who viewed the role model video; 0 for those who viewed the placebo videos. Robust standard errors are presented in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.4: Effect on working at home, full time and earning above median income (conditional on working)

Time after intervention	9 months	12 months	15 months	18 months
	(1)	(2)	(3)	(4)
Panel (a): Effect on working at home				
Treated	0.0297	0.0411	-0.0154	-0.0279
	(0.0365)	(0.0447)	(0.0429)	(0.0532)
Observations	629	493	559	361
Mean(placebo)	0.692	0.540	0.459	0.590
Panel (b): Effect on working full time				
Treated	0.003	0.002	0.009	0.003
	(0.012)	(0.013)	(0.027)	(0.038)
Observations	629	493	559	361
Mean(placebo)	0.975	0.976	0.889	0.867
Panel (b): Effect on earning above median income (USD 81.21)				
Treated	0.0243	0.00614	0.0715*	0.0567
	(0.0304)	(0.0449)	(0.0419)	(0.0540)
Observations	603	456	554	349
Mean(placebo)	0.158	0.427	0.378	0.377

Note: This table displays results from an OLS regression testing treatment effects on type of work, conditional on the woman working. The dependent variable in Panel (a) is a binary variable equal to 1 if the respondent is working at home at the time of the survey, in Panel (b) is a binary variable equal to 1 if the respondent is working full time at the time of the survey, and in Panel (c) is a binary variable equal to one if the respondent's monthly income is equal or more than the median sample income of PKR 10,000 (USD 81.21), all conditional on being employed at the time of the survey. 'Treated' is a binary variable equal to one for respondents who viewed the role model video; 0 for those who viewed the placebo videos. 'Mean (placebo)' is the average value of the dependent variable for the placebo group. Robust standard errors are presented in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.5: Heterogeneous treatment effects on job search and work status over time

Dependent variable:	Job search				Work status			
Time after intervention:	9 months	12 months	15 months	18 months	9 months	12 months	15 months	18 months
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treated	-0.0325	-0.0389	0.00530	0.0163	0.0233	-0.00776	0.0542	0.107***
	(0.0244)	(0.0251)	(0.0251)	(0.0159)	(0.0331)	(0.0372)	(0.0396)	(0.0345)
High-income-education	-0.0558**	-0.0266	0.00486	0.0168	-0.0582*	-0.0989***	0.00858	0.0549*
	(0.0234)	(0.0253)	(0.0242)	(0.0143)	(0.0297)	(0.0331)	(0.0357)	(0.0296)
High-income-education *Treated	0.0730**	0.0420	-0.0196	-0.0310	-0.0451	0.0278	-0.0512	-0.0933**
	(0.0327)	(0.0343)	(0.0339)	(0.0215)	(0.0418)	(0.0467)	(0.0508)	(0.0449)
Observations	1998	1591	1467	1467	1995	1589	1467	1467
Mean high income (placebo)	0.178	0.168	0.143	0.056	0.279	0.253	0.343	0.225
Mean low income (placebo)	0.178	0.141	0.104	0.028	0.314	0.324	0.319	0.167

Note: This table displays results from an OLS regression testing treatment effects on job search efforts and work status. The dependent variable in columns (1) to (4) is a binary variable equal to 1 if the respondent looked for work in the last month. The dependent variable in columns (5) to (8) is a binary variable equal to 1 if the respondent is working at the time of the survey. 'Treated' is a binary variable equal to one for respondents who viewed the role model video; 0 for those who viewed the placebo videos. 'High-income-education' is a binary variable equal to one 1 if the respondent belongs to the high-income-education cluster defined in section 4.3. 'High-income-education*Treatment' is an interaction of 'High-income-education' and 'Treated' group, equal to 1 when the respondent is part of the treated sample and belongs to the high-income-education sub-sample. 'Mean high income (placebo)' and 'Mean low income (placebo)' are the average value of the dependent variable for the high and low income placebo groups, respectively. Robust standard errors are presented in parentheses.

Table A.6: Treatment effects on enrollment, and on job search and work status over time of those not currently enrolled

	(1)	(2)	(3)
Time after intervention:	At 9 months	At 12 months	At 18 months
Panel (a): Effect on enrolment			
Treated	-0.0149	-0.00264	-0.00273
	(0.0198)	(0.0213)	(0.0234)
Observations	2178	1744	1614
Mean (placebo)	0.343	0.296	0.348
Panel (b): Effect on job search, for those not enrolled			
Treated	0.0175	-0.00987	-0.00514
	(0.0198)	(0.0206)	(0.0134)
Observations	1453	1236	1056
Mean (placebo)	0.198	0.172	0.0502
Panel (c): Effect on work status, for those not enrolled			
Treated	0.00147	0.0192	0.0598**
	(0.0235)	(0.0266)	(0.0264)
Observations	1451	1236	1056
Mean (placebo)	0.283	0.305	0.203

Note: This table displays results from an OLS regression testing treatment effects on enrollment in masters, and on job search efforts and work status for those not currently enrolled in a masters programme. We have data on enrollment status at 9, 12 and 18 months after the intervention. The dependent variable in panel (a) is a binary variable equal to 1 if the respondent is enrolled in a masters programme at 9 (column 1), 12 (column 2) and 18 months (column 3). The sample for results in panels (b) - (c) is restricted to those not enrolled in a masters programme at 9, 12 and 18 months. The dependent variable in panel (b) is a binary variable equal to 1 if the respondent looked for work in the last month. The dependent variable panel (c) is a binary variable equal to 1 if the respondent is working at the time of the survey. ‘Treated’ is a binary variable equal to one for respondents who viewed the role model video; 0 for those who viewed the placebo videos. ‘Mean (placebo)’ is the average value of the dependent variable for the placebo group. Robust standard errors are presented in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.7: Job Asaan Outcomes

Variable	(1) Control group	(2) Treatment group	(3) Difference	(4) Count
JA signup	0.215	0.22	0.005	1,087
	(0.41)	(0.41)	(0.03)	
Access EFH	3.253	3.537	0.284	194
	(1.38)	(1.17)	(0.18)	
Exp. Time to Attaining Work(mths)	3.846	4.741	0.895	176
	(3.62)	(4.41)	(0.61)	
Exp. Wage $/month	263.93	263.93	0.002	210
	(0.02)	(0.02)	(0.00)	
Dummy for job search effort in the following ways:				
Applied to prospective employer	0.018	0.017	-0.001	1,087
	(0.133	(0.13)	(0.008)	
Checked at work sites, factories markets	0.025	0.011	-0.014*	1,087
	(0.156)	(0.106)	(0.008)	
Sought assistance from network	0.02	0.027	0.007	1,087
	(0.139)	(0.161)	(0.009)	
Placed or answered advertisements	0.014	0.011	-0.003	1,087
	(0.119)	(0.106)	(0.007)	
Registered with an employment agency	0.007	0.008	0	1,087
	(0.084)	(0.087)	(0.005)	
Applied to any job that individual was matched to by JA	0.113	0.134	0.022	1,087
	(0.317)	(0.341)	(0.02)	
Applied to a job by socio-economic group:				
Poor-Uneducated	0.044	0.052	0.008	919
	(0.205)	(0.222)	(0.014)	
Rich-Educated	0.059	0.049	-0.011	1,364
	(0.237)	(0.215)	(0.012)	

Note: Columns (1) and (2) show the mean value of the variable for the placebo and treatment sample, respectively. Column (3) reports the difference in means between the placebo and treatment; and column (4) displays total number of observations for each variable. We were able to match 1,087 out of the 2500 respondents in our sample with the Job Asaan database. JA signup is a dummy variable for if the respondent completed the second-stage sign-up. 236 had completed the second stage sign-up (‘JA signup’). The measures reported are based on the information stored for these 236 individuals in the Job Asaan database. ‘Access EFH’ is a scale from 1-5 that askes how easy is it for the respondent to come to the facility where Job Asaan’s employment facilitation Hub is located, 1 being extremely likely and 5 being not likely at all. ‘Exp. Time to Attaining Work(mths)’ is the number of months a respondent said they expected to get a job offer. ‘Exp. wage’ is the expected salary respondents expect to get on their next job. ‘Applied to prospective employer’, ‘Checked at work sites, factories, markets’, ‘Sought assistance from network’, ‘Placed or answered advertisements’, ‘Registered with an employment agency’ are all dummy variables for if the respondent undertook these measures for finding a job in the last month. $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

Table A.8: Treatment effects on the spillover group

	(1) Enrolled in Masters	(2) Has created a CV	(3) Job search in the last month	(4) Has a job
Friends with Treated	0.089**	-0.001	0.002	0.034
	(0.04)	(0.04)	(0.03)	(0.05)
Observations	503	503	503	503
Mean (placebo)	0.329	0.584	0.146	0.402

Note: This table displays results from an OLS regression testing spillover effects of the intervention on job market outcomes of networks friends. The dependent variable in column 1 is a binary variable equal to 1 if the respondent is enrolled in Masters at the time of survey , in column 2 the dependent variable is also a binary variable equal to 1 if the respondent has ever created a CV, in column 3 the dependent variable is a binary indicator equal to 1 if the individual in the last 4 weeks has searched for a job and the dependent variable in column 4 is a binary variable equal to 1 if the respondent is working at the time of the survey. ‘Friends with Treated’ is a binary variable equal to one for respondents who are friends with those who viewed the role model video; 0 for those who are friends with those who viewed the placebo videos. The network friends were interviewed in December 2019 i.e. nine months after the baseline. ‘Mean (placebo)’ is the average value of the dependent variable for the placebo group. Robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B Cost of Interbvention

Table B.1 provides a summary of intervention costs. Development costs include the total costs of video development, including payments made to the media company, ContentCre-atorZ and the costs of reminder post cards provided at the time of the repeat intervention. To provide per respondent costs, we divide the cost of the video by the number of partici-pants who were assigned to the treated group at baseline (N = 1275) and the total cost of the post cards provided to respondents treated at the repeat followup (N = 1092). The total development costs is approximately USD 4.54, of which a large portion - that of the video development - is a fixed cost. The per unit cost is expected to fall with larger sample. As such, we assume these estimates to provide an upper limit of the costs that can be incurred with a larger group of participants.

The video and reminder interventions were implemented by a team of enumerators. The enumerators also collected baseline and followup data in the same visit that the video and reminder interventions were implemented. We estimate that a fourth of the time and re-sources of the field team at baseline and a sixth of their time of the second visit were spent on intervention implementation. Included in field team costs are the costs of training, pi-loting, and salaries of enumerators and field supervisors. We assume that the total time spent with treated and placebo participants are not meaningfully different and divide the total costs of implementation at each round by the total number of participants contacted in each round. We estimate the per participant costs amount to USD 4.3 at baseline and USD 0.97 at the time of the repeat intervention, for a total of USD 5.23. Overall the intervention development and implementation cost a total of USD 9.76 per participant.

Table B.1: Activity based costing per study participant (USD 2018)

Activity	(1)	(2)	(3)
Development	Video	Post cards	Total
	4.26	0.28	4.45
Implementation	Baseline	Repeat	Total
	4.25	0.97	5.22
Total			9.77

4.2 Appendix 4.2: Online appendix

A Round-wise Survey Details

A.1 Round One: Baseline

The baseline survey was conducted and intervention implemented between October 2018 and February 2019. We collected basic information from students at this stage including their age, marital status, degree program, their family background and other demographics. We also collected information on their aspirations and expectations regarding work, their work status, their job search effort and other psychological attributes like locus of control, self-efficacy and grit. After they were exposed to the video messages we then asked them questions regarding the video to see how much attention did they pay to the message. Lastly, we also asked them after showing the documentary a series of questions to gauge the growth mindset. All the interviews at baseline were in person and conducted with students on their college campus.

A.2 Round Two: Repeat intervention

The first followup took place from February to May 2019. To reinforce the message of the documentaries, at the first follow-up , all respondents in the treatment group were given post cards that had a motivational message printed on it as giveaways. Treated respondents were also asked questions, as part of the follow-up survey, related to the documentary to test if they remembered the video and the message it conveyed

A.3 Round Three: Followup 1

The second followup was conducted via phone interviews between August and September 2019. By this time students had graduated and were most likely to be engaged in job search.

A.4 Round Four: Followup 2

Round four lasted for two months from December 2019 to January 2020. This again was a short phone survey to find out if the respondents had entered the labour force or not either because they decided to continue further studies, got married or were still actively looking for a job. As a part of this survey we also separately interviewed 503 friends of the treated and placebo samples to see if the treatment had some spillover effects, which we will discuss in section 5. These network friends were identified at the baseline by asking all respondents to share names and contact information of friends in that college who they regularly communicate with.

A.5 Round Five: Followup 3

Finally, the last round of data collection took place from May to June 2020 over the phone. In-person interviews were not possible at this stage due to COVID-19 nation-wide lockdown. We collected data on both the current, as well as retrospective (pre-covid) data from February 2020.

B Additional analysis

Table B.1: Impact of working on attrition in the subsequent survey round

	(1)	(2)	(3)	(4)	(5)	(6)
Months since baseline	9	9	12	12	18	18
Worked in the last round	0.002	-0.005	-0.006	-0.022	-0.023	-0.043
	(0.013)	(0.018)	(0.018)	(0.025)	(0.019)	(0.026)
Treated		-0.004		-0.008		-0.006
		(0.012)		(0.020)		(0.022)
Worked in the last round*T		0.014		0.034		0.041
		(0.025)		(0.037)		(0.039)
Observations	2184	2184	2186	2186	1744	1744

Note: Columns (1)-(2) report attrition from follow-up 1 (9 months after the baseline), columns (3)-(4) from follow-up 2 (12 months after the baseline), and columns (5)-(6) from follow-up 3 (18 months after the baseline). Columns 2, 4 and 6 report results from a regression with controls for treatment status and interaction of work status and treatment status. Work status questions were only asked after graduation, i.e. at 9, 12 and 18 months after baseline. Robust standard errors are presented in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.2: Effect on psychological variables 3 months after treatment

	(1)	(2)	(3)	(4)
	Growth Mindset	Grit	Locus of control	Self efficacy
Treatment	-0.019	-0.107	0.389***	-0.150
	(0.042)	(0.228)	(0.146)	(0.189)
Observations	2185	2185	2185	2184
Mean(placebo)	0.009	41.40	15.762	33.152

Note: This table shows the effects of treatment on the psycho-logical outcomes as measured at the time of the intervention re-inforcement (3 months after the baseline). 'Growth mindset' is a standardized index created out of Implicit Theories of Intelligence scale by Blackwell et al. (2007). 'Locus of control' is a scale from 7-28, constructed from the sum of 7 items, each scored on a 1 to 4 points scale. 'Grit' is also a scale from 12-60, constructed from the sum of 12 items, each scored on a 1 to 5 points. 'Self-efficacy' is a scale from 10-40, constructed from the sum of 10 items, each scored on a 1 to 4 points scale. Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.3: Balance Table

Low-income-education group

Variable	(1) Control group	(2) Treatment group	(3) Difference
Monthly household income (USD)	249.142	257.962	8.820
	(142.580)	(162.087)	(0.382)
Monthly personal income (USD)	25.597	23.912	-1.684
	(69.910)	(80.192)	(0.737)
Dummy: Own house	0.826	0.792	-0.034
	(0.379)	(0.406)	(0.188)
Father's years of education	5.896	5.557	-0.339
	(4.778)	(4.860)	(0.287)
Mother's years of education	2.980	2.726	-0.255
	(3.709)	(3.637)	(0.294)
Dummy: Mother works	0.061	0.055	-0.006
	(0.240)	(0.229)	(0.719)
Public transport	0.732	0.756	0.023
	(0.443)	(0.430)	(0.415)
Dummy: Want to work after graduation	0.881	0.834	-0.048**
	(0.324)	(0.373)	(0.039)
Hours of study per day	4.434	4.374	-0.061
	(2.992)	(3.029)	(0.761)
Hours of housework	3.077	2.814	-0.262*
	(2.582)	(2.215)	(0.098)
Academic performance	7.583	7.468	-0.116
	(1.576)	(1.511)	(0.256)
Dummy: searched for a job	0.048	0.041	-0.007
	(0.215)	(0.199)	(0.597)
Hours of job search in the last 4 months	0.320	0.290	-0.030
	(2.633)	(2.160)	(0.850)
Information about job sites	0.090	0.078	-0.012
	(0.286)	(0.268)	(0.506)
Read job advertisements	0.033	0.026	-0.007
	(0.179)	(0.160)	(0.539)
Online job search	0.035	0.009	-0.026***
	(0.184)	(0.093)	(0.006)
Household size	7.303	7.339	0.036
	(2.176)	(2.128)	(0.797)
Observations	456	463	919

Note: Columns (1) and (2) show the mean value of the variable in the row for the placebo and treatment sample, for the low-income-education group (as defined in section 4.3), only. Column (3) reports the difference in means between the placebo and treated sample ($***p < 0.01$, $**p < 0.05$, $*p < 0.1$); and column (4) displays total number of observations for each variable. Standard deviations are reported in the parentheses.

Table B.4: Balance Table

High-income-education group

Variable	(1) Control group	(2) Treatment group	(3) Difference
Monthly household income (USD)	354.009	363.705	9.696
	(229.902)	(251.962)	(0.458)
Monthly personal income (USD)	29.717	27.598	-2.120
	(99.837)	(87.630)	(0.680)
Dummy: Own house	0.837	0.828	-0.009
	(0.370)	(0.378)	(0.653)
Father's years of education	11.831	11.664	-0.167
	(3.554)	(3.790)	(0.402)
Mother's years of education	10.848	10.717	-0.131
	(3.132)	(3.245)	(0.448)
Dummy: Mother works	0.103	0.083	-0.021
	(0.305)	(0.276)	(0.193)
Public transport	0.822	0.779	-0.042**
	(0.383)	(0.415)	(0.049)
Dummy: Want to work after graduation	0.840	0.865	0.024
	(0.367)	(0.342)	(0.206)
Hours of study per day	4.313	4.476	0.163
	(2.947)	(3.173)	(0.327)
Hours of housework	2.929	2.997	0.068
	(2.039)	(2.325)	(0.567)
Academic performance	7.429	7.371	-0.057
	(1.397)	(1.442)	(0.457)
Dummy: searched for a job	0.052	0.047	-0.005
	(0.223)	(0.212)	(0.663)
Hours of job search in the last 4 months	0.239	0.152	-0.087
	(2.090)	(0.790)	(0.319)
Information about job sites	0.110	0.126	0.016
	(0.314)	(0.332)	(0.360)
Read job advertisements	0.014	0.032	0.018**
	(0.119)	(0.176)	(0.028)
Online job search	0.029	0.031	0.002
	(0.167)	(0.172)	(0.824)
Household size	5.970	6.030	0.060
	(1.541)	(1.519)	(0.468)
Observations	707	657	1,364

Note: Columns (1) and (2) show the mean value of the variable in the row for the placebo and treatment sample for the high-income-education group (as defined in section 4.3), only. Column (3) reports the differ-ence in means between the placebo and treated sample ($***p < 0.01$, $**p < 0.05$, $*p < 0.1$); and column (4) displays total number of observations for each variable. Standard deviations are reported in the parentheses.

Table B.5: Descriptive statistics By group

Variable	(1) Low-income -education	(2) High-income -education	(3) Difference	(4) Count
Panel (a): Household Characteristics				
Monthly household income (USD)	253.585	358.679	105.094***	2,283
	(152.700)	(240.740)	(8.953)	
Household size	7.321	5.999	-1.322***	2,283
	(2.151)	(1.530)	(0.077)	
Dummy: Own house	0.809	0.833	0.024	2,280
	(0.393)	(0.373)	(0.016)	
Father's years of education	5.725	11.751	6.025***	2,283
	(4.820)	(3.669)	(0.178)	
Mother's years of education	2.852	10.785	7.933***	2,283
	(3.673)	(3.186)	(0.145)	
Dummy: Mother works	0.058	0.093	0.035***	2,222
	(0.234)	(0.291)	(0.012)	
Panel (b): Own characteristics				
Dummy: Want to work after graduation	0.857	0.852	-0.005	2,282
	(0.350)	(0.355)	(0.015)	
Hours of study per day	4.404	4.392	-0.012	2,279
	(3.009)	(3.058)	(0.130)	
Hours of housework	2.945	2.962	0.017	2,282
	(2.406)	(2.181)	(0.097)	
Dummy: searched for a job	0.045	0.050	0.005	2,283
	(0.207)	(0.218)	(0.009)	
Hours of job search in the last 4 months	0.305	0.197	-0.108	2,281
	(2.406)	(1.602)	(0.084)	
Monthly personal income (USD)	24.748	28.699	3.951	2,250
	(75.230)	(94.143)	(3.742)	
Observations	919	1,364	2,499	

Note: Columns (1) and (2) show the mean value of the variable in the row for the low-income-education and the high-income-education sample (as defined in section 4.3) respectively. Column (3) reports the difference in means between the columns (1) and (2). ($***p < 0.01$, $**p < 0.05$, $*p < 0.1$); and column (5) displays total number of observations for each variable. Standard deviations are reported in the parentheses. Panel (a) provides outcomes measures at the household level and Panel (b) provides average characteristics of the respondent.

Table B.6: Heterogeneous treatment effect on above median income over time

Time after intervention:	9 months	12 months	15 months	18 months
	(1)	(2)	(3)	(4)
Treated	-0.0422	0.486	0.0610	0.0303
	(0.0432)	(1.260)	(0.0707)	(0.0947)
High-income-education	-0.0163	0.0652	-0.0453	-0.0932
	(0.0453)	(1.186)	(0.0652)	(0.0920)
High-income-education*Treated	0.125*	-0.577	0.0423	0.0672
	(0.0649)	(1.670)	(0.0928)	(0.121)
Observations	554	422	499	321
Mean(placebo)	0.158	-0.424	0.378	0.377

Note: This table displays results from an OLS regression testing treatment effects on monthly income, conditional on the woman working. The dependent variable is a binary variable equal to one if the respondent's monthly income is USD 81.21 or more; 0 otherwise at the time of the survey. 'Treated' is a binary variable equal to one for respondents who viewed the role model video; 0 for those who viewed the placebo videos. 'High-income-education' is a binary variable equal to one 1 if the respondent belongs to the high-income-education cluster defined in section 4.3. 'High-income-education*Treatment' is an interaction of 'High-income-education' and 'Treated' group, equal to 1 when the respondent is part of the treated sample and belongs to the high-income-education sub-sample. 'Mean (placebo)' is the average value of the dependent variable for the placebo group. Robust standard errors are presented in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.7: Job search by subject majors

Time after intervention:	9 months	12 months	15 months	18 months
	(1)	(2)	(3)	(4)
Treated	0.0197	-0.0173	-0.0126	0.00327
	(0.0207)	(0.0207)	(0.0217)	(0.0135)
Social science major	0.0210	0.0355	0.00639	0.0123
	(0.0225)	(0.0239)	(0.0241)	(0.0151)
Social science major * Treated	-0.000438	0.00470	0.0186	-0.0114
	(0.0317)	(0.0329)	(0.0331)	(0.0210)
Observations	2189	1746	1614	1614
Mean(placebo)	0.171	0.154	0.128	0.0461

Note: This table displays results from an OLS regression testing treatment effects on job search efforts. The dependent variable is a binary variable equal to 1 if the respondent looked for work in the last month. 'Treated' is a binary variable equal to one for respondents who viewed the role model video; 0 for those who viewed the placebo videos. 'Social science major' is an indicator variable for student taking any of the social sciences subjects as their majors, 0 is for humanities. 'Social science major * Treated' is an interaction of 'Social science major' and 'Treated'. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.8: Work status by subject majors

Time after intervention:	9 months	12 months	15 months	18 months
	(1)	(2)	(3)	(4)
Treated	-0.00292	0.0150	0.0606*	0.0419
	(0.0259)	(0.0300)	(0.0327)	(0.0285)
Social science major	0.0527*	0.00968	0.0823**	0.0284
	(0.0277)	(0.0307)	(0.0341)	(0.0287)
Social science major * Treated	-0.00378	-0.00776	-0.0858*	0.00733
	(0.0388)	(0.0436)	(0.0479)	(0.0420)
Observations	2186	1744	1614	1614
Mean(placebo)	0.290	0.277	0.338	0.201

This table displays results from an OLS regression testing treatment effects on work status. The dependent variable is a binary variable equal to 1 if the respondent looked for work in the last month. 'Treated' is a binary variable equal to one for respondents who viewed the role model video; 0 for those who viewed the placebo videos. 'Social science major' is an indicator variable for student taking any of the social sciences subjects as their majors, 0 is for humanities. 'Social science major * Treated' is an interaction of 'Social

science major' and 'Treated'. Standard errors in parentheses. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.9: Heterogeneous treatment effects on the spillover group

	(1) Enrolled in Masters	(2) Has created a CV	(3) Job search in the last month	(4) Has a job
Friends with Treated	0.103**	-0.0198	-0.00240	0.0327
	(0.0490)	(0.0497)	(0.0375)	(0.0528)
High-income-education	0.0395	-0.0570	0.0259	0.00359
	(0.0527)	(0.0534)	(0.0403)	(0.0568)
High-income-education*	-0.0196	-0.0419	-0.0184	-0.0291
Friends with Treated	(0.0590)	(0.0597)	(0.0451)	(0.0636)
Observations	464	464	464	464
Mean (placebo)	0.329	0.584	0.147	0.402

Note: This table displays results from an OLS regression testing spillover effects of the intervention on job market outcomes of friends of the main sample. 'Friends with Treated' is a binary variable equal to one for respondents who were friends with those who viewed the role model video; 0 for those who were friends with those who viewed the placebo videos. We exclude those who were reported as friends of both the treated and placebo groups. 'Enrolled in masters' is a binary variable equal to 1 if the respondent is enrolled in a Masters program at the time of survey, 'has created a CV' is a binary variable equal to 1 if the respondent has ever created a CV, 'Job search in the last month' is a binary indicator equal to 1 if the individual searched for a job in the last 4 weeks and the dependent variable in column 4 is a binary variable equal to 1 if the respondent is working at the time of the survey. 'High-income-education' is a binary variable equal to one 1 if the respondent were friends with those who belong to the high-income-education cluster defined in section 4.3. 'High-income-education*Friends with' is an interaction of 'High-income-education' and 'Friends with Treated' group, equal to 1 when the respondent is friends with those treated individuals who belonged to the high-income-education sub-sample.The network friends were interviewed in followup-1 i.e. nine months after the baseline. 'Mean (placebo)' is the average value of the dependent variable for the placebo group. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

C Balanced Panel Results

Table C.1: Descriptive Statistics

	(1) Placebo	(2) Treatment	(3) Difference	(4) Obs
Panel (a): Household characteristics				
Monthly household income (USD)	314.047	324.982	10.935	1,315
	(211.482)	(237.927)	(12.397)	
Dummy: Own house	0.815	0.808	-0.007	1,440
	(0.388)	(0.394)	(0.021)	
Household size	6.527	6.646	0.119	1,444
	(1.933)	(1.948)	(0.102)	
Father's years of education	9.481	9.360	-0.121	1,444
	(5.006)	(5.161)	(0.268)	
Mother's years of education	7.865	7.647	-0.218	1,444
	(5.083)	(5.264)	(0.272)	
Dummy: Mother works	0.091	0.063	-0.029**	1,408
	(0.288)	(0.243)	(0.014)	
Panel (b) Own characteristics				
Dummy: Want to work after graduation	0.833	0.844	0.011	1,444
	(0.373)	(0.363)	(0.019)	
Dummy: Married	0.087	0.079	-0.009	1,444
	(0.283)	(0.269)	(0.015)	
Hours of study per day	4.276	4.336	0.060	1,441
	(2.912)	(2.930)	(0.154)	
Hours of housework per day	2.895	2.791	-0.104	1,443
	(2.130)	(2.091)	(0.111)	
Dummy: Searched for a job	0.050	0.043	-0.007	1,444
	(0.218)	(0.203)	(0.011)	
Hours of job search in the last 4 months	0.243	0.166	-0.077	1,443
	(2.069)	(1.008)	(0.087)	
Monthly personal income (USD)	27.405	27.536	0.131	1,423
	(82.372)	(90.550)	(4.584)	
Observations	744	700	1,444	

Note: Columns (1) and (2) show the mean value of the variable in the row for the placebo and treatment . sample, respectively, for the balanced sample of students who appear in all survey rounds. Column (3) reports the difference in means between the placebo and treatment sample ($***p < 0.01$, $**p < 0.05$, $*p < 0.1$); and column (4) displays total number of observations for each variable. Standard deviations are reported in the parentheses. Panel (a) provides outcomes measures at the household level and Panel (b) provides average characteristics of the respondent.

Table C.2: Attrition, including baseline characteristics

	(1)	(2)	(3)
Treated	-0.015	-0.017	-0.120
	(0.019)	(0.021)	(0.124)
Monthly household income (USD)		-0.000	-0.000
		(0.000)	(0.000)
Dummy: Own house		-0.069**	-0.061
		(0.027)	(0.039)
Household size		0.008	0.006
		(0.006)	(0.008)
Father's years of education		-0.002	-0.005
		(0.003)	(0.004)
Mother's years of education		0.005*	0.005
		(0.003)	(0.004)
Dummy: Mother works		-0.003	0.054
		(0.039)	(0.052)
Dummy: Want to work		-0.001	-0.034
after graduation		(0.030)	(0.043)
Dummy: Married		-0.029	0.026
		(0.038)	(0.054)
Hours of study per day		0.001	-0.001
		(0.005)	(0.006)
Hours of housework		-0.014**	-0.014*
		(0.006)	(0.008)
Dummy: searched for a job		0.066	0.057
		(0.057)	(0.076)

Hours of job search in	-0.011**	-0.008
the last 4 months	(0.006)	(0.007)
Monthly personal income (USD)	0.000	-0.000
	(0.000)	(0.000)
Monthly household income (USD) *T		0.000
		(0.000)
Dummy: Own house *T		-0.013
		(0.054)
Household size *T		0.002
		(0.011)
Father’s years of education *T		0.005
		(0.005)
Mother’s years of education *T		-0.000
		(0.005)
Dummy: Mother works *T		-0.128
		(0.078)
Dummy: Want to work		0.059
after graduation *T		(0.060)
Dummy: Married *T		-0.112
		(0.075)
Hours of study per day *T		0.003
		(0.009)
Hours of housework per day *T		-0.002
		(0.011)
Dummy: searched for a job *T		0.047
		(0.119)
Hours of job search		-0.009

in the last 4 months *T			(0.012)
Monthly personal			0.000
income (USD) *T			(0.000)
Constant	0.585***	0.627***	0.687***
	(0.013)	(0.063)	(0.088)
p(F-stat)		0.682	0.726
Mean	0.578	0.579	0.579
Observations	2499	2183	2183

Note: The dependent variable is 1 if the respondent participated in all survey rounds and 0 otherwise. Results in column (2) are from a regression with controls for household characteristics (monthly household income, dummy for own house, household size, father's yeas of education, mother's years of education, and dummy for mother works) and respondents' own characteristics (dummies for if wants to work after graduation, and is married, hours of study and housework per day, dummy for if searched for job, hours of job search in the last 4 months, and monthly personal income). Results in column (3) are from a saturated regression with the same controls as in column 2 and the interaction of these controls with the treatment dummy ('T'). All covariates are collected before the intervention is implemented. Observations are lower in columns 2 and 3 due to missing observations in baseline characteristics. Robust standard errors are presented in parentheses. 'p(F-stat)' refers to the p-value of F-Statistic from a test of joint significance of the controls in column 2 and interaction of treatment status and baseline characteristics in column 3. 'Mean' refers to the average level of attrition. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.3: Post intervention treatment effects

	(1) Transport index	(2) Growth mindset
Treated	0.597***	0.139***
	(0.0652)	(0.0533)
Observations	1444	1444
Mean (placebo)	-0.291	-0.066

Note: This table displays results from an OLS regression testing treatment effects on outcomes measured after intervention implementation on the bal-anced sample of students who appear in all survey rounds. 'Transporta-tion index' is an index measuring respondents absorption with the video, following Banerjee et al. (2019). 'Growth mindset' is a standardized in-dex created out of Implicit Theories of Intelligence scale by Blackwell et al. (2007).'Treated' is a binary variable equal to one for respondents who viewed the role model video; 0 for those who viewed the placebo videos. 'Mean (placebo)' is the average value of the dependent variable for the placebo group. Robust standard errors are presented in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.4: Effect on job search and work status over time

Dependent variable:	Job search				Work status			
Time after intervention:	9 months	12 months	15 months	18 months	9 months	12 months	15 months	18 months
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treated	0.019	-0.010	0.001	-0.000	-0.019	0.005	0.021	0.042^{*}
	(0.019)	(0.018)	(0.017)	(0.010)	(0.030)	(0.031)	(0.032)	(0.028)
Observations	1444	1444	1444	1444	1444	1444	1444	1444
Mean (placebo)	0.188	0.160	0.128	0.045	0.305	0.289	0.340	0.204

Note: This table displays results from an OLS regression testing treatment effects on job search efforts and work status on the balanced panel of . students who appear in all survey rounds. The dependent variable in columns (1) to (4) is a binary variable equal to 1 if the respondent looked for work in the last month. The dependent variable in columns (5) to (8) is a binary variable equal to 1 if the respondent is working at the time of the survey. 'Treated' is a binary variable equal to one for respondents who viewed the role model video; 0 for those who viewed the placebo videos. 'Mean placebo)' is the average value of the dependent variable for the placebo group. Robust standard errors are presented in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.5: Effect on job search index components (conditional on searching)

Time after intervention	9 months	12 months	15 months	18 months
	(1)	(2)	(3)	(4)
Panel (a): Job search hours				
Treated	0.848	0.0266	2.707	11.72
	(1.298)	(0.878)	(4.058)	(14.57)
Observations	283	223	185	65
Mean (placebo)	9.807	7.437	7.695	9.735
Panel (b): Read job ads				
Treated	0.0600	0.0663	-0.123	-0.0431
	(0.0514)	(0.0711)	(0.0757)	(0.171)
Observations	283	223	185	65
Mean (placebo)	0.179	0.420	0.442	0.412
Panel (c): Search via informal networks				
Treated	0.0379	0.0551	0.0762	-0.00610
	(0.0505)	(0.0564)	(0.0661)	(0.172)
Observations	283	223	185	65
Mean (placebo)	0.779	0.798	0.747	0.676
Panel (d): Online job search				
Treated	0.0242	-0.0388	-0.0154	0.148
	(0.0591)	(0.0682)	(0.0768)	(0.119)
Observations	283	223	185	65
Mean (placebo)	0.543	0.597	0.568	0.735
Panel (e): Formal job search				
Treated	0.0299	-0.0174	-0.0794	0.0214
	(0.0629)	(0.0700)	(0.0775)	(0.161)
Observations	283	223	185	65
Mean (placebo)	0.457	0.538	0.558	0.294

Note: This table displays results from an OLS regression testing treatment effects on job search efforts on balanced sample of students who appear in all survey rounds and report having looked for a job in the last 4 weeks. The dependent variable in panel is the approximate number of hours they spent on job search during the last 4 weeks, the dependent variables in panels (b) - (e) are binary variables for different activities the respondents undertook to look for a job where 'Read job ads' is a binary indicator variable for respondents who have read job advertisements while looking for a job over the past 4 weeks. 'Search via informal networks' is an indicator variable for respondents who have asked family members, friends, colleagues etc. for a job, 'Online job search' is an indicator variable for respondents who have searched for or responded to job advertisements online while looking for a job over the past 4 weeks, 'Formal job search' is an indicator variable for respondents who have contacted potential employers, temporary employment agencies or the public employment service while searching for a job over the past 4 weeks. 'Treated' is a binary variable equal to one for respondents who viewed the role model video; 0 for those who viewed the placebo videos. * p < 0.10** p < 0.05, *** p < 0.01.,

Table C.6: Effect on working at home, full time and earning more than median income (conditional on working)

Time after intervention	9 months	12 months	15 months	18 months
	(1)	(2)	(3)	(4)
Panel (a): Effect on working at home				
Treated	0.0631	0.0499	-0.0361	-0.0425
	(0.0458)	(0.0490)	(0.0451)	(0.0573)
Observations	427	420	504	325
Mean (placebo)	0.678	0.530	0.462	0.592
Panel (b): Effect on working full time				
Treated	-0.000198	-0.0116	-0.00699	-0.0187
	(0.0151)	(0.0139)	(0.0275)	(0.0389)
Observations	427	420	504	325
Mean (placebo)	0.978	0.986	0.897	0.882
Panel (b): Effect on earning above median income (USD 81.21)				
Treated	0.0123	-0.00200	0.0946**	0.0828
	(0.0387)	(0.801)	(0.0439)	(0.0570)
Observations	410	392	499	314
Mean (placebo)	0.175	-0.0550	0.369	0.372

Note: This table displays results from an OLS regression testing treatment effects on type of work, conditional on the woman working for the balanced panel of students who appear in all survey rounds. The dependent variable in Panel (a) is a binary variable equal to 1 if the respondent is working at home at the time of the survey, in Panel (b) is a binary variable equal to 1 if the respondent is working full time at the time of the survey, and in Panel (c) is a binary variable equal to one if the respondent's monthly income is equal or more than the median sample income of PKR 10,000 (USD 81.21), all conditional on being employed at the time of the survey. 'Treated' is a binary variable equal to one for respondents who viewed the role model video; 0 for those who viewed the placebo videos. 'Mean (placebo)' is the average value of the dependent variable for the placebo group. Robust standard errors are presented in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table C.7: Descriptive statistics By group

Variable	(1) Low-income-education	(2) High-income-education	(3) Difference	(4) Count
Panel (a): Household Characteristics				
Monthly household income ($)	261.54	355.86	94.32***	1,315
	(164.09)	(248.87)	(12.44)	
Own house	0.796	0.813	0.018	1,313
	(0.404)	(0.390)	(0.022)	
Household size	7.333	6.044	-1.288***	1,315
	(29.009)	(20.616)	(1.371)	
Father's years of education	5.738	11.727	5.988***	1,315
	(4.789)	(3.784)	(0.238)	
Mother's years of education	2.966	10.911	7.945***	1,315
	(3.729)	(3.285)	(0.196)	
Mother works	0.050	0.100	0.049***	1,280
	(0.219)	(0.300)	(0.016)	
Panel (b): Own characteristics				
Want to work after graduation	0.853	0.853	0.000	1,315
	(0.355)	(0.354)	(0.020)	
Study time	4.331	4.316	-0.015	1,314
	(2.811)	(2.982)	(0.165)	
Hours of housework	2.704	2.945	0.241**	1,314
	(1.935)	(2.089)	(0.115)	
Searched for a job	0.047	0.050	0.003	1,315
	(0.212)	(0.217)	(0.012)	
Job search hours	0.183	0.236	0.053	1,314
	(1.085)	(2.002)	(0.097)	
Monthly personal income ($)	26.90	27.48	0.0575	1,301
	(83.52)	(90.83)	(5.01)	
Observations	510	805		

Note: Columns (1) and (2) show the mean value of the variable in the row for the low-income-education and the high-income-education sample (as defined in section 4.3) respectively, in the balanced panel. Column (3) reports the difference in means between the columns (1) and (2). ($***p < 0.01$, $**p < 0.05$, $*p < 0.1$); and column (5) displays total number of observations for each variable. Standard deviations are reported in the parentheses. Panel (a) provides outcomes measured at the household level and Panel (b) provides average characteristics of the respondent.

Table C.8: Balance Table: Low-income-education group

Variable	(1) Control group	(2) Treatment group	(3) Difference
Monthly household income ($)	253.43	269.92	16.48
	(152.25)	(175.39)	(0.002)
Monthly personal income ($)	26.54	27.28	0.75
	(71.34)	(94.69)	(0.007)
Own house	0.802	0.789	-0.013
	(0.399)	(0.409)	(0.707)
Father's years of education	5.859	5.614	-0.246
	(4.762)	(4.822)	(0.563)
Mother's years of education	3.131	2.795	-0.336
	(3.786)	(3.669)	(0.309)
Mother works	0.048	0.053	0.005
	(0.214)	(0.224)	(0.798)
Public transport	0.714	0.793	0.079**
	(0.453)	(0.406)	(0.040)
Want to work after graduation	0.865	0.841	-0.024
	(0.343)	(0.367)	(0.441)
Study time	4.344	4.319	-0.025
	(2.852)	(2.775)	(0.920)
Hours of housework	2.865	2.538	-0.327*
	(2.198)	(1.608)	(0.056)
Academic performance	7.610	7.428	-0.182
	(1.572)	(1.472)	(0.178)
Searched for a job	0.050	0.044	-0.006
	(0.219)	(0.205)	(0.735)
Job search hours	0.174	0.192	0.018
	(0.856)	(1.281)	(0.850)
Information about job sites	0.112	0.096	-0.016
	(0.316)	(0.295)	(0.546)
Read job advertisements	0.047	0.024	-0.022
	(0.211)	(0.154)	(0.173)
Online job search	0.039	0.008	-0.031**
	(0.193)	(0.089)	(0.023)
Family size	7.266	7.402	0.135
	(2.178)	(2.172)	(2.174)
Observations	259	251	510

Note: Columns (1) and (2) show the mean value of the variable in the row for the placebo and treatment sample, for the low-income-education group (as defined in section 4.3), only in the balanced sample. Column (3) reports the difference in means between the placebo and treated sample ($***p < 0.01$, $**p < 0.05$, $*p < 0.1$); and column (4) displays total number of observations for each variable. Standard deviations are reported in the parentheses. Panel (a) provides outcomes measured at the household level and Panel (b) provides average characteristics of the respondent.

Table C.9: Balance Table: High-income-education group

Variable	(1) Control group	(2) Treatment group	(3) Difference
Monthly household income ($)	351.27	360.90	9.63
	(233.22)	(265.18)	(0.005)
Monthly personal income ($)	26.06	24.04	2.98
	(88.03)	(93.88)	(0.005)
Own house	0.824	0.802	-0.022
	(0.381)	(0.399)	(0.430)
Father's years of education	11.754	11.697	-0.058
	(3.650)	(3.930)	(0.830)
Mother's years of education	10.967	10.850	-0.116
	(3.125)	(3.455)	(0.616)
Mother works	0.125	0.072	-0.053**
	(0.331)	(0.259)	(0.013)
Public transport	0.834	0.779	-0.055**
	(0.373)	(0.416)	(0.048)
Want to work after graduation	0.838	0.870	0.031
	(0.368)	(0.337)	(0.210)
Study time	4.247	4.392	0.145
	(2.912)	(3.058)	(0.493)
Hours of housework	2.888	3.008	0.119
	(1.905)	(2.275)	(0.418)
Academic performance	7.425	7.432	0.007
	(1.391)	(1.435)	(0.943)
Searched for a job	0.055	0.044	-0.010
	(0.228)	(0.206)	(0.500)
Job search hours	0.316	0.148	-0.167
	(2.662)	(0.792)	(0.236)
Information about job sites	0.124	0.143	0.020
	(0.329)	(0.351)	(0.411)
Read job advertisements	0.019	0.044	0.025**
	(0.137)	(0.206)	(0.041)
Online job search	0.036	0.031	-0.005
	(0.186)	(0.174)	(0.717)
Family size	5.995	6.098	0.1037
	(1.513)	(1.536)	(1.524)
Observations	421	384	805

Note: Columns (1) and (2) show the mean value of the variable in the row for the placebo and treatment sample, for the high-income-education group (as defined in section 4.3), only in the balanced sample. Column (3) reports the difference in means between the placebo and treated sample ($***p < 0.01$, $**p < 0.05$, $*p < 0.1$); and column (4) displays total number of observations for each variable. Standard deviations are reported in the parentheses. Panel (a) provides outcomes measured at the household level and Panel (b) provides average characteristics of the respondent.

Table C.10: Heterogeneous treatment effect on job search over time

Time after intervention:	9 months	12 months	15 months	18 months
	(1)	(2)	(3)	(4)
Treated	-0.036	-0.027	0.009	0.019
	(0.032)	(0.028)	(0.026)	(0.016)
High-income-education	-0.072**	-0.013	0.003	0.021
	(0.03)	(0.03)	(0.03)	(0.014)
High-income-education*Treated	0.079*	0.029	-0.009	-0.030
	(0.04)	(0.04)	(0.04)	(0.022)
Observations	1315	1315	1315	1315
Mean (placebo)	0.188	0.16	0.128	0.0457

Note: This table displays results from an OLS regression testing treatment effects on job search efforts on balanced sample of students who appear in all survey rounds. The dependent variable is a binary variable equal to 1 if the respondent looked for work in the last month. `Treated' is a binary variable equal to one for respondents who viewed the role model video; 0 for those who viewed the placebo videos. `High-income-education' is a binary variable equal to one 1 if the respondent belongs to the high-income-education cluster defined in section \ref{hetero}. Due to missing values on household income at baseline that were used for the k-means clustering analysis, the sample for this analysis is 1315 instead of the balanced panel sample of 1444. `High-income-education*Treatment' is an interaction of `High-income-education' and `Treated' group, equal to 1 when the respondent is part of the treated sample and belongs to the high-income-education sub-sample.`Mean (placebo)' is the average value of the dependent variable for the placebo group. Robust standard errors are presented in parentheses. \sym{*} \(p<0.10\), \sym{**} \(p<0.05\), \sym{***} \(p<0.01\)

Table C.11: Heterogeneous treatment effect on work status over time

Time after intervention:	9 months	12 months	15 months	18 months
	(1)	(2)	(3)	(4)
Treated	-0.003	-0.003	0.066	0.101***
	(0.042)	(0.041)	(0.042)	(0.037)
High-income-education	-0.060	-0.077**	0.022	0.062*
	(0.037)	(0.037)	(0.038)	(0.031)
High-income-education*Treated	-0.024	0.010	-0.068	-0.094*
	(0.052)	(0.052)	(0.054)	(0.048)
Observations	1315	1315	1315	1315
Mean (placebo)	0.305	0.289	0.340	0.204

Note: This table displays results from an OLS regression testing treatment effects on work status on balanced sample of students that appears in all survey rounds. The dependent variable is a binary variable equal to 1 if the respondent is working at the time of the survey. ‘Treated’ is a binary variable equal to one for respondents who viewed the role model video; 0 for those who viewed the placebo videos. ‘High-income-education’ is a binary variable equal to 1 if the respondent belongs to the high-income-education cluster defined in section 4.3. Due to missing values on household income at baseline that were used for the k-means clustering analysis, the sample for this analysis is 1315 instead of the balanced panel sample of 1444. ‘High-income-education*Treatment’ is an interaction of ‘High-income-education’ and ‘Treated’ group, equal to 1 when the respondent is part of the treated sample and belongs to the high-income-education sub-sample. ‘Mean (placebo)’ is the average value of the dependent variable for the placebo group. Robust standard errors are presented in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.12: Heterogeneous treatment effect on above median income over time

Time after intervention:	9 months	12 months	15 months	18 months
	(1)	(2)	(3)	(4)
Treated	-0.0883	-0.939	0.0848	0.0367
	(0.0560)	(0.983)	(0.0745)	(0.0999)
High-income-education	-0.0636	-0.825	-0.00925	-0.0908
	(0.0581)	(1.167)	(0.0666)	(0.0940)
High-income-education*Treated	0.165**	1.594	0.0326	0.0806
	(0.0812)	(1.195)	(0.0971)	(0.125)
Observations	377	359	453	291
Adjusted R^2	0.083	0.019	0.054	0.032
Mean(placebo)	0.175	-0.0550	0.369	0.372

Note: This table displays results from an OLS regression testing treatment effects on monthly income, conditional on the woman working for the balanced sample of students that appears in all survey rounds. The dependent variable is a binary variable equal to one if the respondent's monthly income is USD 81.21 or more; 0 otherwise at the time of the survey. 'Treated' is a binary variable equal to one for respondents who viewed the role model video; 0 for those who viewed the placebo videos. 'High-income-education' is a binary variable equal to one 1 if the respondent belongs to the high-income-education cluster defined in section 4.3. 'High-income-education*Treatment' is an interaction of 'High-income-education' and 'Treated' group, equal to 1 when the respondent is part of the treated sample and belongs to the high-income-education sub-sample. 'Mean (placebo)' is the average value of the dependent variable for the placebo group. Robust standard errors are presented in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.13: Treatment effects on enrollment, and on job search and work status over time of those not currently enrolled

	(1)	(2)	(3)
Time after intervention:	At 9 months	At 12 months	At 18 months
Panel (a): Effect on enrolment			
Treated	-0.00563	0.00375	-0.00306
	(0.0245)	(0.0236)	(0.0246)
Observations	1435	1442	1444
Mean (placebo)	0.348	0.302	0.351
Panel (b): Effect on job search, for those not enrolled			
Treated	0.0133	-0.00311	-0.00308
	(0.0251)	(0.0237)	(0.0143)
Observations	942	1010	942
Mean (placebo)	0.214	0.180	0.0497
Panel (c): Effect on work status, for those not enrolled			
Treated	-0.0220	0.0153	0.0571**
	(0.0293)	(0.0298)	(0.0280)
Observations	942	1010	942
Mean (placebo)	0.301	0.319	0.203

Note: This table displays results from an OLS regression testing treatment effects on enrollment in masters, and on job search efforts and work status for those not currently enrolled in a masters programme, from the balanced panel of students that appears in all survey rounds. We have data on enrollment status at 9, 12 and 18 months after the intervention. The dependent variable in panel (a) is a binary variable equal to 1 if the respondent is enrolled in a masters programme at 9 (column 1), 12 (column 2) and 18 months (column 3). The sample for results in panels (b) - (c) is restricted to those not enrolled in a masters programme at 9, 12 and 18 months. The dependent variable in panel (b) is a binary variable equal to 1 if the respondent looked for work in the last month. The dependent variable panel (c) is a binary variable equal to 1 if the respondent is working at the time of the survey. 'Treated' is a binary variable equal to one for respondents who viewed the role model video; 0 for those who viewed the placebo videos. 'Mean (placebo)' is the average value of the dependent variable for the placebo group. Robust standard errors are presented in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.14: Job search by subject majors

Time after intervention:	9 months	12 months	15 months	18 months
	(1)	(2)	(3)	(4)
Treated	0.0211	-0.0156	-0.0106	0.00327
	(0.0274)	(0.0238)	(0.0229)	(0.0143)
Social science major	0.0137	0.0366	0.0106	0.0128
	(0.0289)	(0.0267)	(0.0255)	(0.0160)
Social science major * Treated	-0.00550	0.00719	0.0220	-0.00809
	(0.0405)	(0.0369)	(0.0351)	(0.0224)
Observations	1444	1444	1444	1444
Mean(placebo)	0.188	0.160	0.128	0.0457

Note: This table displays results from an OLS regression testing treatment effects on job search efforts on the balanced sample of students that appears in all survey rounds. The dependent variable is a binary variable equal to 1 if the respondent looked for work in the last month. ‘Treated’ is a binary variable equal to one for respondents who viewed the role model video; 0 for those who viewed the placebo videos. ‘Social science major’ is an indicator variable for student taking any of the social sciences subjects as their majors, 0 is for humanities. ‘Social science major * Treated’ is an interaction of ‘Social science major’ and ‘Treated’. Standard errors in parentheses. *p<0.10, **p<0.05, ***p<0.01

Table C.15: Work status by subject majors

Time after intervention:	9 months	12 months	15 months	18 months
	(1)	(2)	(3)	(4)
Treated	-0.00125	0.0154	0.0539	0.0351
	(0.0328)	(0.0336)	(0.0350)	(0.0305)
Social science major	0.0795^{**}	0.0259	0.0667^{*}	0.0294
	(0.0345)	(0.0342)	(0.0360)	(0.0305)
Social science major * Treated	-0.0378	-0.0223	-0.0685	0.0114
	(0.0481)	(0.0484)	(0.0509)	(0.0446)
Observations	1444	1442	1444	1444
Mean(placebo)	0.305	0.289	0.340	0.204

This table displays results from an OLS regression testing treatment effects on work status on the balanced sample of students that appears in all survey rounds. The dependent variable is a binary variable equal to 1 if the respondent looked for work in the last month. ‘Treated’ is a binary variable equal to one for respondents who viewed the role model video; 0 for those who viewed the placebo videos. ‘Social science major’ is an indicator variable for student taking any of the social sciences subjects as their majors, 0 is for humanities. ‘Social science major * Treated’ is an interaction of ‘Social science major’ and ‘Treated’. Standard errors in parentheses. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

D Post Documentary Discussion

The women you just saw in this video faced numerous challenges in their life like Ayesha and Hira had to come from really far to complete their education, Rida had to adjust to a career that is very unusual for women to adopt, Soniya had to balance both her work and family life but due to their devotion and commitment to their goals they successfully over-came all those challenges.[39] They did not fear from setbacks they faced instead they learnt from them. Today because of what they have achieved in their life their families take pride in them and their standing in the household and household welfare has improved. They have graduated from colleges just like yours and come from very humble backgrounds but they have fought with the circumstances they faced and today they have managed to se-cure gainful employment and have successful careers. You also can have it all but it only comes with effort, devotion and perseverance. You can learn a lot from these women's lives like:

- Things do not always go your way and people around you may not always support you but if you persist and persevere you can achieve your dreams. Do not allow others' estima-tion of yourself define you, let others' false judgements inspire you and push you forward instead.

- If you want to achieve something in life you are going to have to step out of your comfort zone. Growth and comfort do not coexist.

- Your family is your support network, winning their trust and confidence gives you strength and the energy to reach your goals. Women even if they work can successfully balance both their work and family life through efficiently managing their time and through pru-dence.

Please reflect upon what you saw in this video, analyze what you already have and where you lack, try to apply the lessons learnt on your life too if you envision yourself a success-ful woman in the future.

[39] 7Note that the names of the women have been changed in order to maintain confidentiality.

E Job Asaan Flyer

Figure E1: Job Asaan Flyer