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Women's Work, Social Norms and the Marriage Market*

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Abstract

While it is well-acknowledged that the gendered division of labor *within* marriage adversely affects women's allocation of time to market work, there is less evidence on how extant social norms can influence women's work choices *pre-marriage*. We conduct an experiment on an online marriage market platform that allows us to measure preferences of individuals in partner selection in India. We find that employed women are 14.5% less likely to receive interest from male suitors relative to women who are not working. In addition, women employed in 'masculine' occupations are 3.2% less likely to elicit interest from suitors relative to those in 'feminine' occupations. Our results highlight the strong effect of gender norms and patriarchy on marital preferences, especially for men hailing from higher castes and northern India, where communities have more traditional gender norms. These findings suggest that expectations regarding returns in the marriage market may influence women's labor market participation and the nature of market work.

JEL Codes: J12, J16, J24

Keywords: social norms, work choices, marriage market, gender, India

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1 Introduction

A nascent literature in economics has analysed factors which influence partner matching (in dating and marriage markets), including the differences in male and female preferences for partner characteristics from a social or evolutionary perspective. Men typically place a higher value on physical beauty (Fisman *et al.*, 2006), while women emphasize male income and earnings (Fisman *et al.*, 2006; Chiappori *et al.*, 2021). Moreover, men do not value women's intelligence or ambition when it exceeds their own (Fisman *et al.*, 2006), whereas women look for male partners who outdo them on attributes such as income or height Chiappori *et al.* (2021). This literature has overwhelmingly been situated within a perspective that attempts to unravel how partner selection is linked to biological evolution (see Abramova *et al.* (2016) for a review of the literature in psychology and sociology), with some exceptions. However, there is limited empirical evidence on how marriage market preferences may reinforce cultural biases and influence labor market decisions before marriage, thereby perpetuating observed gender gaps in economic outcomes.

Historically, parental preferences have played a major role in partner selection in arranged marriages, reinforcing social stereotypes and norms (see Anukriti & Dasgupta (2017) for a review). For example, Banerjee *et al.* (2013) and Dugar *et al.* (2012) find strong caste based preferences in arranged marriages in Bengal, India. While social norms on marriages within social (or caste) networks are salient, there is less evidence on how gender norms play out in the marriage market or whether they perpetuate when new matching technology allows younger generations to be more active participants in decisions related to partner selection. For instance, digital platforms are increasingly being adopted both for dating and marriage, providing an opportunity to analyse individuals' partner preferences.

We conduct an online experiment that allows us to measure preferences of individuals, as a proxy for their eventual match, on a digital matching platform in the Indian marriage market. In the spirit of correspondence studies, often conducted in economics in the context of labor markets (Baert, 2018; Bertrand & Duflo, 2017; Neumark, 2018), dating and marriage markets (Ong & Wang, 2015; Dugar *et al.*, 2012; Banerjee *et al.*, 2013), we create and observe profiles for women and men on a leading matrimonial platform in India to elicit responses or 'interests' from potential partners on the platforms. Unlike newspaper ads that limit observation of individual preferences, matrimonial websites offer an alternative to both traditional print media as well as parental networks to find a spouse through low search costs and relative anonymity in expressing partner preferences (Bapna *et al.*, 2016; Dhar, 2021). Moreover, matrimonial websites are finding rapid and widespread adoption among the youth and their families in India (Kaur & Palriwala, 2014).[1]

We vary the characteristics of the profiles, first, by current working status. Second, conditional on the profile being currently employed, we classified occupations into three categories - 'feminine' (e.g. school teacher), 'masculine' (e.g. technical supervisor) and gender 'neutral' (e.g. data entry operator) based on the proportion of women workers in these occupations. The occupation gender stereotypes represent the extent of social acceptance of women's work choices as per extant gender roles, particularly norms that place the burden of home production on women. In addition, for profiles of employed women, we vary their stated preference to work or not after marriage. Finally, within each work status category, we vary profiles by caste (e.g. Brahmins, Other high castes, Scheduled Castes) and education (e.g. Diploma, Bachelors and Masters) groups.

We tailor the full set of profiles to two cities - Delhi (North India) and Bangalore (South India) - to assess any effects of spatial heterogeneity in patriarchal and gender norms which has been extensively documented to be more regressive and stringent in the north relative to the south of the country (Dyson & Moore, 1983; Rahman & Rao, 2004). The dimensions of physical attributes (e.g. height), family characteristics (e.g. number and gender of siblings), household income and individual earnings (if applicable) are held constant across profiles.

Our results highlight the strong effect of gender norms and patriarchy on marital pref-

[1]From a single website set up in 1996, there are now more than 1500 such partner matching platforms (Pal, 2011) in India. 90% of 20-30 year olds report using matrimonial platforms, which had more than 50-55 million online users by 2013 (ASSOCHAM).

erences. On average, employed women are 14.5% less likely to receive interests from male suitors relative to women who are not working. The higher preference for female partners who are not working, holds across all education groups. Moreover, women employed in 'masculine' occupations are 3.2% less likely to receive interests as compared to women employed in 'feminine' occupations. Lastly, a woman in a masculine job who prefers to continue to work after marriage is less likely to elicit male interest, relative to a woman in a feminine job who wants to continue working. Most importantly, these results are driven by responses from higher caste men in north India (Delhi), where patriarchal norms are more salient.

While our study is restricted to an online matrimonial site which has users who have above-average education and wealth, in comparison to the urban population in India, the heterogeneity analyses show that our estimates are likely to provide a lower bound for the population. We find that less educated women are more likely to receive such a penalty and that less educated men are more likely to place the penalty on working women. This indicates that the marriage market penalty on working women may be higher in the population (in India) than on the platform itself.

The above results extend the existing literature to factors that affect partner choices beyond an evolutionary perspective and show that cultural factors may perpetuate stereotypes of an 'ideal' wife. Moreover, our findings are in contrast to those for more developed countries. Neyt *et al.* (2019) find neither gender uses job status or job prestige as a determinant of whom to show initial interest to on Tinder but males less frequently begin a conversation with females who are unemployed. On the other hand, we show that existing patriarchal and gender norms that constrain women's roles to within the household can be a strong determinant of partner preferences in developing country contexts. Our results extend Dhar (2021), who finds that women who signal wanting to work after marriage receive up to 22% less interest from men on a marriage-market matching platform in and around Delhi than those women who have never worked or are willing to give up work after marriage. Further, while current research acknowledges the role of gendered division of labor in married women's lower allocation of time to the labor market across countries (Hochschild & Machung, 2012; Blair & Lichter, 1991; Bianchi, 2011; Afridi *et al.*, 2022b), our experiment suggests that expectations regarding returns in the marriage market may influence women's decisions regarding labor market participation and the nature of work *before* marriage.

We also contribute to the literature on marriage market gaps across skilled and educated women. Hwang (2016) and Bertrand *et al.* (2016) find that highly educated or skilled women marry at a lower rate relative to less educated or less skilled women. However, these trends have been changing differentially across countries. While this gap has reversed in North America, it has either persisted or increased in East Asia and parts of Europe. Bertrand *et al.* (2016) argue that negative attitudes towards working women might contribute to the lower marriage rate of skilled women due to bargaining over household production (Fernández *et al.*, 2004). While these studies rationalize the marriage gap, our paper shows how social norms and attitudes can causally affect the demand for working women in the marriage market. In fact, we extend this further by showing that occupational choices can also result in the observed gap in marital rates.

Lastly, our findings extend the literature on occupational segregation by gender and its persistence over time (Cortes & Pan, 2018). The literature on occupations and identity shows that the existence of gender-job associations in a society can lead men and women to take on gender typical roles at the workplace (Akerlof & Kranton, 2000). There is also evidence that women prefer flexible workplaces (Mas & Pallais, 2017) and value workplaces with greater safety which increases with a higher share of female workforce (Folke & Rickne, 2022). Our results show that a higher marital preference for women working in such occupations can also explain the observed segregation. These novel findings demonstrating marital preferences for employed women in 'feminine' occupations may also be driven by marital expectations around gendered division of household and domestic care work. In general, feminine occupations or female dominated occupations are associated with lighter or more flexible work schedules and may be perceived as allowing women to balance responsibilities of home production and market work (Goldin, 2014).[2] The revealed male preference in the marriage market for occupations with greater presence of women employees can also lead to potential loss in earnings for women as these occupations are typically associated with relatively lower wages (Mas & Pallais, 2017; Goldin, 2014). This holds in India too, where occupations dominated by women workers, on average, pay 30% lower daily wages than male dominated occupations (Periodic labor Force Survey, 2018-19).[3]

In the next section we discuss the background and context of our study, followed by our experiment design and the data in Section 3. Section 4 outlines the estimation strategy, while the results are presented in Section 5. We highlight the heterogeneity of our findings by region and caste in Section 6, followed by discussion of results and conclusions in Sections 7 and 8, respectively.

2 Background and context

In this section we first elaborate on the context of our study. The proportion of working age women who are employed has been low and stagnant at nearly 22%-24% in urban India (National Sample Surveys, various rounds) over the last three decades. This is stark when compared to 90% employment rate for urban men, despite education disparities closing across gender. Afridi *et al.* (2022b) show that differential contribution of men and women towards home production plays an important role in explaining the gender gap in employment. We, thus, focus on the specific norm of gender-based division of labor wherein women bear a disproportionate burden of home production, which is likely to be correlated with other

[2] Globally, women spend triple the time on unpaid care work than men, ranging from 1.5-2.2 in North America and Europe to 6-6.8 times longer in Middle East-North Africa and South Asia (OECD). In urban India women spend almost 7.5 times more time on domestic work as compared to married men (Afridi *et al.*, 2022b). Given the near universality of marriage in India, these marital preferences around women's work may have important implications for the low and stagnant female labor force participation rates in urban India (at 20% for the last three decades, PLFS 2017-18), despite increases in female education (Afridi *et al.*, 2022b).

[3] Women dominated occupations are classified as those in 75th percentile or above, and male dominated as those in lower than 25th percentile of the distribution of proportion of female employees in the labor market.

gender norms that restrict women's physical mobility and social interactions, such as sexual purity.[4] Furthermore, India provides a unique setting where gender norms are known to differ both spatially and across socio-economic groups or castes.

2.1 Gender gap in intra-household time allocation

Throughout this section we discuss data on the time allocation of married, urban men and women aged 20-45 years using nation-wide survey data. These data indicate the prevailing norms regarding the time allocation of women post-marriage.

Existing literature shows that married women in urban India bear a disproportionate burden of household chores and spend little time in the labor market despite high wage returns (Afridi *et al.*, 2022b). Figure 1, panel (a), plots the average time spent per day in the labor market by gender across education levels using the nationally representative Time Use Survey (TUS) data collected between January and December 2019. Married women with or less than primary education spend close to 2 hours per day in the labor market, whereas those with secondary and higher secondary education spend about half that time and those with diploma and graduate education spend around 2 hours a day again. This rises to almost 3 hours per day for women with postgraduate and above education. On the other hand, time spent in the labor market is much higher ($\approx$ 9 hours per day) for men at all education levels.

The gender gap in time allocation reverses for home production activities. Figure 1, panel (b) shows gender differences in urban India, by education levels, on time spent on domestic work. Men (irrespective of education) spend only one hour per day undertaking household work whereas women spend nearly 8-9 hours per day. These data, thus, show that while an increase in education does not monotonically increase labor force engagement for women, the time spent on domestic and care work remains almost constant across women's education

[4] In general, women's access to the labor market can be restricted by social norms related to time allocation for unpaid domestic and care work within the home, as well as norms around sexual purity. These factors can also affect occupational choices of women. For instance, taboos related to interactions between opposite sexes can lead to a preference for occupations where there is a significant proportion of women co-workers.

levels. Importantly, this U-shape of women's labor force participation (LFP) with education cannot be explained by returns to education (Afridi *et al.*, 2022b).[5]

Using the latest two quarters of data for the Consumer Pyramids Household Survey (CPHS) (from September to December 2021 and from January to April 2022), we examine the relationship between married individuals time use, employment status and occupation type.[6] First, we find that employed women spend 60-70% less time on domestic work, relative to women who are not in the work force (Appendix Table A.1). Next, we examine whether women working in male dominated occupations, gender neutral occupations or those not working, spend a differential amount of time on domestic work when compared to women in female dominated occupations.[7] Appendix Table A.2 shows that women who are not working spend 50%-60% more time on domestic work in comparison to women employed in female dominated occupations. On the other hand, women in male dominated occupations and women in gender neutral occupations spend 50%-60% and 10%-18% less time on domestic work relative to women in female dominated occupations, respectively. Clearly, women in male dominated occupations spend the least amount of time on domestic work compared to their female peers, possibly suggesting that these occupations are characterized by more

[5]Appendix Figure A.1 plots the daily wages earned by working women and men across each education level using the Periodic Labor Force Survey (PLFS) in 2018-19. Clearly, there is a huge increase in wage returns for both women and men as their education increases from higher secondary to Diploma (by 15%) and Graduate (by 24% over diploma) and Postgraduate (by 27% over graduates) for women. However, the working hours for women first fall and then rise as women's education increases from Diploma and above, though the average levels are still low. Afridi *et al.* (2022b) show that a part of this muted response of married women to increase in labor market returns with education can be explained by higher home and market productivity with own education and households' desire to a produce a socially bench-marked level of the home good.

[6]Unfortunately, TUS data do not provide information on the occupation of women working in the labor market. The CPHS data from the Centre for Monitoring Indian Economy (CMIE) - a nationwide, household-level panel data where each household is interviewed once every quarter of a year - provides data on both time use and employment details of the respondent such as their occupation along with data on individual and household socio-demographics. The stark gender contrast of men spending much more time in the labor market and women spending almost 3 times as much time as men on household work, clearly stands out using the CPHS data as well, as shown in Figure 1, Panel (c) and (d).

[7]These occupation classifications are arrived at by using the proportion of female workers in each occupation and examining its distribution across occupations. We take the occupations at $\approx$ 70th percentile or above of the distribution of female workers as female dominated and 35th percentile or below as male dominated. The median for female proportion across occupations is 6%. We also try 25th and 75th percentiles are results remain similar but given that 25th percentile is 0 in the CPHS data, we prefer the current specification.

demanding or inflexible working schedules (Goldin, 2014). We also find that daily wage rate decreases as proportion of women workers increase in an occupation (Appendix Figure A.2.[8] This is in line with the existing literature on compensating wage differentials which finds higher wages in inflexible or more demanding vs flexible or less demanding jobs (Goldin, 2014).

2.2 Heterogeneity in gender gaps

Dyson & Moore (1983) contrast states in the north of India with the southern states on patriarchal and gender related outcomes. They note that the south is characterized by later age at marriage, lower marital fertility, higher labor market participation and, in general, a higher status of women.[9] They hypothesize that kinship structures, such as endogamous marriage in the south, result in higher female autonomy in the region. Other studies point at differences in historical cropping patterns across Indian regions, with cultivation of rice more prevalent in the south and demand for greater female labor in rice cultivation, as a contributing factor to greater value on women's labor in the south (Bardhan, 1974).[10] More recently, Singh *et al.* (2022) construct an Index of Patriarchy of Indian states using the Nationally Family Health Survey (NFHS-4, 2015-16) and reconfirm the Dyson & Moore (1983) cultural divide between north and south India.

The above spatial heterogeneity accompanies higher women's labor force participation in the south relative to the north (Boserup, 1970; Dyson & Moore, 1983; Chen, 1995; Das, 2006;

[8] We use the Periodic labor Force Survey (PLFS-2018) data to plot the daily wages since the CPHS data did not collect data on hours or days worked by an individual until 2020.

[9] Recent data from the NFHS-4 conducted in 2015-16 confirms these patterns. In urban India, age at marriage is 19.5 in north India vs 20.1 in the south for women (NFHS-4) while for men it is 24 in the north and 25.7 in the south. We use NFHS-4 for aggregates across states since in NFHS-5 different states were sampled over different time periods during the pandemic. Data for urban India from Census 2011 also shows that sex ratio defined as females per 1000 males was 970 in the south vs 897 in the north and women's years of education were 7.5 in the south while 6.6 in the north. Gender gaps in education are also lower in the south, with years of education of women 85% that of men in the south and 80% that of men in the north. Clearly the gender disparities among urban married men and women aged 20-45 are lower in the south.

[10] Alesina *et al.* (2013) show that societies with greater use of plough placed higher value on male labor relative to female labor.

Mahajan & Ramaswami, 2017).[11] We test this hypothesis using the nationally representative Time Use Survey (TUS, 2019) and find that in the north, women spend more time on domestic work relative to men in comparison with the south (Appendix Table A.3, columns 1 and 3). Similarly, we find that in the north, women spend relatively less time than men in the labor market (columns 2 and 4) in comparison with their southern peers.[12] The gender gaps in time spent on market and domestic work are thus larger and more unequal in north India.

Additionally, higher household social status is associated with women who are not working in the labor market in India. Existing literature shows that such norms are more stringent for upper caste households (Eswaran *et al.*, 2013). Using the TUS (2019), we find that women belonging to higher castes spend less time in the labor market and more time undertaking domestic work (Appendix Table A.4). These findings underscore the salience of spatial and caste based differences in gender norms within India.

2.3 The marriage market

Marriage is near universal in India - 98% women and 94% men aged 30 were ever-married in 2018-19 in urban India (PLFS 2018-19). The median age at first marriage was 20.1 and 26.5 years, for women and men respectively in urban India in 2019-21 (NFHS-5).[13] At the same time, labor force participation (LFP) rates of urban women have been low and stagnant at 22% but stand nearly at 100% for men, for the past three decades (authors' own calculation using National Sample Surveys and Periodic Labor Force Surveys).

The importance of matchmaking by families in India, also known as "arranged" marriage, is well recognized. Indian Human Development Survey shows that 95% marriages in urban India are arranged (Kaur & Palriwala, 2014), with only a marginal decline over

[11] We follow the classification used in Dyson & Moore (1983) for the grouping of Indian states into 'north' and 'south'. The north includes the states of Gujarat, Rajasthan, Uttar Pradesh, Madhya Pradesh, Punjab, and Haryana while the south includes Kerala, Tamil Nadu, Andhra Pradesh, Karnataka, and Maharashtra.

[12] These patterns also hold with the CPHS data. The results are omitted for brevity.

[13] In India, 95% of women have had at least one child upon marriage.

the last decade (Allendorf & Pandian, 2016). A recent Lok Foundation-Oxford University survey in 2018 among 20-30 years old married youth also showed that 90% married through the custom of arranged marriage. This prevalence was larger in the northern states vs the southern states. Moreover, matchmaking is evolving from a traditionally in-person process with direct community and family involvement, to one with more indirect technologically enabled matching and mediation such as matrimonial websites, which allow for greater selection of marriage partners to fulfil a diverse list of desirable characteristics in a spouse (Kaur & Palriwala, 2014). While the proportion of marital matches via matrimonial platforms is unknown, in 2012-13 around 50-55 million users were registered on matrimonial websites in India with a projected year-on-year increase of about 130% since then (The Print). The industry has grown rapidly to include more than 1500 such websites. (Pal, 2011), and 90% of 20-30 year olds in urban India have reported looking for a spouse online (ASSOCHAM). These figures show that arranged marriages dominate in India with matrimonial websites playing an increasing role over time. This is largely owing to wider selection, free or low fees, simplicity, privacy and ease of online websites. As a result, traditional avenues for arranged marriages like newspaper ads have been falling in importance.

Matrimonial websites allow for prospective suitors to post profiles, using standardized templates, with information on age, gender, city, profession, income, religion, education, lifestyle choices (e.g. diet, smoking, drinking), family type, family values and status. Apart from the standard details, users have an opportunity to provide more information on themselves and the desired characteristics in a spouse. Most of these matrimonial websites take great pains to stress differences from dating websites and discourage non-serious users (Kaur & Palriwala, 2014). Matrimonial websites offer the ability to use search functions and also offer potential matches and recommendations, based on sophisticated algorithms. A study of 1300 profiles registered in a day on a major national website found that the users were mostly below 35, from a mix of metropolitan and non-metropolitan cities, reportedly from upper middle or middle class families with an income of INR 50,000-3,00,000 per month

(Kaur & Palriwala, 2014).

To understand the characteristics of the users on the matrimonial platform that we utilize for the experiment, we compare the demographics of never married profiles on the platform with that of the never married population in the two states which contain Delhi and Bangalore using the PLFS data from 2018-19. For the comparison, we keep only women aged 18 and above and men aged 21 and above, since these are are the minimum legal age for marriage by gender in India. We also restrict the PLFS sample to individuals who have at least completed schooling since this is the minimum education level on the platform. Appendix Table A.5 reports the average age, annual income, education and proportion of Scheduled Caste (SC) on the platform in September 2020 (when the profiles were scraped for the first time before carrying out the experiment) and the Periodic labor Force Survey in 2018-19. On average, men on the platform are older (30.5 years on the platform vs 25.5 years in the population), more educated (93% are graduate or higher on the platform vs 65% in the population) and have higher income conditional on employment (almost four times higher than the population). Proportion of SC men are also lower on the platform as compared to the PLFS. We find similar patterns for women in Panel B, with women on the platform being older, more educated and earning higher income when employed. Thus, this matrimonial platform largely caters to relatively more educated and middle to upper-middle class families even among the demographic group of individuals who have completed schooling. We discuss the external validity of our findings later.

3 Experiment design

We conducted an experiment on a leading online match-making platform in India, with over 0.4 million active users in a given month. We uploaded fictitious female and male profiles on the platform between June and August 2021. The females profiles varied by working status i.e., a female profile would either be working in the labor market (employed) or not working (unemployed). Further, within the employed female profiles we allowed the occupations to vary by gender stereotypes. To do this, we categorized occupations into three groups - female dominated or 'Feminine' (e.g. primary school teacher), 'Neutral' (e.g. data entry operator) and male dominated or 'Masculine' (e.g. machine technician). The details of the procedure used to arrive at these categories is discussed in greater detail below. Lastly, for each employed-occupation female profile we indicated whether she preferred to work or not after marriage. Thus, in total one unemployed female profile and six female employed profiles (varying by three occupations and two categories of preference to work post marriage) were uploaded onto the platform. We further varied each profile (irrespective of work status) by education levels - Diploma, Bachelors of Arts and Master of Arts. This led to a total of *21* female profiles.[14] Figure 2 depicts our experiment design for the female profiles.

To ensure that the profiles were realistic, we tailored the occupation of an employed female profile to her level of education by analyzing the nationally representative Periodic Labor Force Survey (PLFS 2018-19) of India. We estimated the share of women employed across occupation categories by education (Appendix Figure A.3).[15] We then shortlisted 20 occupations which broadly fit into the three education categories: Diploma, BA and MA levels of education. These occupations were classified using the average urban female workforce participation into (1) female dominated ('Feminine'), (2) comparable gender composition ('Neutral') and (3) male dominated ('Masculine'). On average, women constitute 22% of the total workforce in urban areas of India. Based on the above criteria, we shortlisted occupations where women constituted more than 50% of employees, as per the PLFS, into the first category of 'Feminine', where they constituted between 15-35% of the workforce into the second category and where they constituted less than 10% of the workforce into the third category ('Masculine' occupations).[16]

[14]All the fabricated profiles belonged to Hindu religion since this is the predominant religion (80% of the population) in India and most marriages are within religion. Only 2.2% of married women between the age of 15-49 report marrying outside their religion in 2005 (India Human Development Survey 2004-5).

[15]We kept only those occupations for which at least 50% of the employed individuals had completed schooling since the platform caters to individuals with at least this level of education .

[16]In the PLFS 2018-19, 50% of female employees stands at $\approx$ 75th percentile and 10% of female employees

Finally, we chose nine occupations from this set across the three education categories, to reflect each stereotype within each education category.[17] These were selected on the basis of being distinct in terms of female presence, with gradations along the education spectrum and available to students graduating in an Arts degree so that gender differences across STEM and non-STEM major choices could be mitigated. For instance, the category of 'Teachers' was chosen under the *Feminine* category but the level of teaching varied along the education spectrum - Kindergarten teacher (Diploma), Primary School teacher (BA), Senior School teacher (MA). Similarly, factory related work was chosen to represent *Masculine* occupations: Machine technician (Diploma), Line supervisor (BA) and Floor supervisor (MA). Lastly, the gender neutral occupations - Data entry operator (Diploma), Bank teller (BA), Bank manager (MA) - also varied by education levels.

Lastly, to take into account the variation in gender norms in India across castes and the fact that most marriages in India are within the same caste, we varied the fictitious profiles by caste.[18] We classified the profiles into the following three caste categories - Brahmins (Upper Castes), Other high castes (OHC), Scheduled Castes (SC).[19] Thus, in total we created $21 \times 3 = 63$ female profiles and uploaded them on the matchmaking platform.[20]

The other characteristics of the profiles, e.g. age, height, manager of the profile, num-

stands at $\approx$ 25th percentile of the distribution of female workers. To avoid occupations that were too close to the cutoffs for the masculine and feminine defined occupations, we take 15%-35% as the bandwidth for gender-neutral occupations for the purpose of classifying the fictitious female profiles.

[17] Our occupation-gender classification is also supported by a survey we conducted amongst undergraduate and graduate students (18+ age group, who are likely to be actively dating and would soon be entering the labor market as well as looking for marriage partners in some years) that corroborates gendered perceptions of occupations with the proportions of male and female workers reported in the employment data. The survey respondents were asked - "Please rate the degree of maleness/femaleness generally associated with each job listed below." on a scale of $1-5$, where 1 represented masculine jobs and 5 represented feminine jobs, defined by the proportion of women typically employed in these occupations. Our findings indicate that actual employment distributions by gender match the gender stereotyping of occupations.

[18] In 2011, 5.82% of all marriages were inter-caste (Ray *et al.*, 2020).

[19] In general there are five major caste categories in India - Brahmins (Upper Castes), Other high castes (OHC), Other Backwards Classes (OBC), Scheduled castes (SC) and Scheduled Tribes (ST). We do not include STs in our profiles because while most STs report their religion as Hinduism, they are heterogeneous and distinctive and hence are not usually considered a part of the *varna* system. Also, sub-castes included under the OBC category have been changing over time (Mint). Given the fluidity in the definition of the OBC's we do not include them as a caste category in our analyses.

[20] Appendix Table A.6 shows the characteristics of all the scraped profiles from the platform, including those which were divorced/widowed, by gender.

ber of siblings and composition, household income range and own income range (for those employed) were held constant across profiles. None of the fictitious profiles carried a photograph. The details on profile creation and the value assigned to each of these dimensions are provided in Appendix B. These values were chosen based on the average characteristics of the majority of existing (non-fictitious) female profiles on the platform (Appendix Table A.6) so that the profiles we created were realistic.

These profiles were created for two cities consecutively, first for Delhi (North India) and then Bangalore (in the state of Karnataka in South India), i.e., the residential location listed for a profile was either of these two cities.[21] The choice of these two cities was based on the cultural divide between the North and the South of India as discussed previously (Dyson & Moore, 1983; Rahman & Rao, 2004). As mentioned earlier, we varied the profiles along three caste categories - Brahmin (Upper-castes), Other High Castes (OHC) and Scheduled Castes (SC) for each residential location. The matrimonial platform provided a pre-defined list of caste categories. The aggregate categories of Brahmin (High Caste) and socio-economically disadvantaged Scheduled Castes (SC) existed in the list. However, only sub-categories of 'Other high caste' were provided. We chose these sub-categories to be *Bania* for Delhi and *Vokkaliga* for Bangalore since these are the dominant groups within 'Other high castes' in the two cities.

We followed the same process for creation of the fictitious male profiles except that there was no stated preference for work after marriage by these profiles. Given the above design there were 63 female profiles and 36 male profiles uploaded for each city, consecutively. 3-4 randomly chosen profiles were uploaded daily. Each profile was put up on the marriage market platform for a month and deleted 30 days after the date of posting. Information was collected on interests (an invitation to connect on the platform) for each fictitious female (male) profile on a weekly basis and at the end of the profile's 30-day life.

[21] While the profiles in each city were created consecutively, there was some overlap in the timing of profiles uploaded towards the end of the experiment in Delhi and its start in Bangalore, since each profile was online for a month.

3.1 Data

Our analysis is restricted to data on responses to the fictitious female profiles. The fictitious male profiles did not elicit much interest from women on the platform, consistent with existing research which indicates that typically men are more likely to make the first move to initiate a relationship (Karmegam, 2020; Fiore *et al.*, 2010; Xia *et al.*, 2014).[22]

Table 1 shows the average proportion of (real) male interests received by our fictitious female profiles on the match-making platform over a month. We assume that all male profiles who interacted with any of our fictitious female profiles in a city were potential male suitors for all the female profiles we created for that city.[23] Overall, 4762 and 1199 male profiles expressed an interest for at least one fictitious female profile posted in Delhi and Bangalore, respectively. The higher number of male profiles expressing an interest in the female profiles we created in Delhi is indicative of a higher base of user profiles of men in Delhi on the platform.[24] On average, a fictitious female profile received expressions of interest from 6.2% males.

Next, we examine the proportion of male profiles that demonstrated interest based on the employment status and occupation type of the female profiles we created. On average, women profiles which stated 'not-working' as the employment status received the most attention and interest with positive responses from 7% of male profiles, while female profiles working in

[22] Using data from online match-making platforms in India Karmegam (2020) find that for every expression of interest received by men, on average, women received 40 expressions of interest. This feature of the dating markets has also been observed in the context of the U.S. (Fiore *et al.*, 2010) and China (Xia *et al.*, 2014) where women were found to reach out more selectively than men - of the total contacts established on the dating platform, 77.1% consisted of a man initiating contact with a woman while 22.9% consisted of a woman contacting a man. In our study, a male profile received slightly less than one expression of interest whereas a female profile received 185 expressions of interest, on average, over a one month period.

[23] While we do not observe who viewed the fictitious profiles, it must be noted that in the context of this match-making platform 'profile views' may not be an effective variable to determine whether a potential male suitor considered a given female in his choice set or not. This is because the platform gives an option to those registered on the platform to declare preferred spouse characteristics along certain dimensions like religion, caste, education, employment, and habits like smoking, drinking and dietary preferences. For instance, if a male suitor on the platform prefers females of his caste then it is possible that he is not shown the profiles of women who belong to other castes or shown such profiles in later ordering preference. Thus, instead of using profile views, we use the entire set of interacting male profiles to create a set of potential suitors.

[24] On average, of the total male profiles listed on the platform 10.7% were from Delhi and 4.8% from Bangalore.

feminine, gender-neutral and masculine occupations received lower interest at 6.2%, 6.17% and 6% from male profiles, respectively. These statistics show that there are perceptible differences in the expression of men's interest based on the employment status of a female profile. Lastly, we find that among employed female profiles, there does not seem to be much difference in the interest received by those who prefer to work after marriage relative to those who are open to giving up their job after marriage.

Across caste categories, high caste (Brahmins and others) fictitious female profiles received expressions of interest from 6.7% and 6.9% of the male profiles, respectively, while scheduled caste (SC) female profiles received lower interest at 5.1% from male profiles. Across the education levels of the created female profiles, those with a BA and MA degree as their highest education received expressions of interest from 6.3% and 6.5% male profiles, while those with a Diploma received fewer expressions of interest at 5.9% from male profiles. The characteristics of the (non-fictitious) male profiles on the platform who sent expressions of interest to the created female profiles are reported in Appendix Table A.7.

4 Estimation strategy

We estimate whether fictitious female profiles who were working received any differential display of interest from potential male suitors on the platform using the specification below:

$$Y_{icsj} = \beta_0 + \beta_1 Working_i + \beta_2 Education_i + \gamma_{cs} + X_j + \epsilon_{icsj} \tag{1}$$

where Y is an indicator variable that takes a value one if fictitious female profile i of caste c in city s received an expression of interest i.e., an invitation to connect on the platform, from a (non-fictitious) male profile j registered on the online marriage platform; $Working$ is an indicator variable that equals one if the fictitious female profile is working or employed and zero otherwise. As discussed earlier, if a male user on the platform sent an expression of interest to any fictitious female profile in city s, that user is considered to be a potential male suitor or interest seeker on that platform for that city.

In all specifications, we control for the fictitious female profile's education, caste and city of residence. Caste by city fixed effects (γ_{cs}) control for the possibility that caste composition of potential male suitors can be different across cities and this may lead to differences in interest received across the female profiles we created. Additionally, we control for a host of characteristics of the (non-fictitious) male profiles which express an interest with the female profiles we posted on the platform (X_j). These include caste category, age, height, profile manager (self-managed or managed by parents, relatives or friends), income, highest level of education attained and whether the reported income of the male profile is less than the corresponding female profile. The coefficient of interest β_1 is the difference (in percentage points) between the probability of receiving an expression of interest by women who are employed in the labor market versus those who are not employed. If the estimated effect is negative (positive) then it is indicative of a lower (higher) interest for women who are currently working in the labor market as compared to women who are not working, from male profiles on the platform. The standard errors of the estimates are clustered at the male suitor level.

In the next specification, we examine whether expressions of interest by male profiles differ across occupational categories of the fictitious female profiles, using the following specification:

$$Y_{icsj} = \beta_0 + \delta_1 Masculine_i + \delta_2 Neutral_i + \delta_3 Not\ working_i + \beta_2 Education_i + \gamma_{cs} + X_j + \epsilon_{icsj} \quad (2)$$

where $Masculine$ is an indicator variable that takes a value of one if the female profile is indicated as working in a 'masculine' occupation and zero otherwise; $Neutral_i$ takes a value of one if the female profile is shown to be working in a gender-neutral occupation and zero otherwise; $Not\ working$ takes a value of one if the female profile is described as not employed/working in the labor market. The coefficient δ_1 shows the difference in percentage points between the probability of receiving an expression of interest by women employed in masculine occupations in comparison to women employed in feminine occupations. Similarly, δ_2 shows the difference (in percentage points) between the probability of receiving an expression of interest by women employed in gender-neutral occupations in comparison to women employed in feminine occupations. The coefficient δ_3 shows the difference (in percentage points) between the probability of receiving an expression of interest by women who are not working versus those working in a feminine occupation.

5 Results

Table 2 shows the estimates from Equation 1 for both cities overall in column (1) and disaggregated for Delhi and Bangalore in columns (2) and (3), respectively. On average, a female profile receives expressions of interest from 6.2% male suitors on the platform. However, working or employed female profiles receive 0.9 percentage points fewer responses, i.e., on average they receive interests from 5.3% men. This translates into a penalty of 14.5% in terms of interests from male suitors. However, the city-wise results in columns (2) and (3) show that this effect is large and significant in Delhi alone, where employed female profiles are 17% less likely to receive a response relative to their unemployed peers. On the other hand, the effect is negligible and insignificant in Bangalore. Thus, working women are indeed less likely to receive expressions of interest on the marriage platform but this effect is not homogeneous - the preference for non-working female partners stems from Delhi in North India, where conservative gender norms are stronger compared to the south.

Next, we investigate whether the type of occupation - either gender neutral or gender stereotypical (i.e.'masculine' or 'feminine') - affects the expressions of interest received by female profiles on the matchmaking platform by estimating Equation 2. Table 3, column (1) shows that female profiles employed in 'masculine' occupations are 0.2 percentage points or

3.2% less likely to receive an expression of interest compared to those employed in ‘feminine’ occupations. There is no effect or difference in interest received by female profiles employed in neutral vis-a-vis those in ‘feminine’ occupations. Additionally, female profiles which indicate ‘not working’ receive 0.8 percentage points or 12.9% more responses than women employed in ‘feminine’ occupations. Again, results in columns (2) and (3) for Delhi and Bangalore show that these results are driven predominantly by the female profiles created in Delhi. The magnitude of these effects is larger in Delhi where women in ‘masculine’ occupations and females who are not employed receive 5.1% lower and 15.2% greater interest respectively, as compared to women employed in ‘feminine’ occupations.

How do these findings vary by women who prefer to continue working after marriage, relative to those who are amenable to not working after marriage? Table 4 reports the results obtained for the subset of employed female profiles. The base category is female profiles employed in ‘feminine’ jobs who are willing to leave their job after marriage. The results in column (1) show that there is no differential effect for female profiles employed in ‘masculine’ occupations, and there is a positive effect for those in gender-neutral jobs, when female profiles signal openness to leaving work after marriage. However, there is a significant decrease in the probability of receiving an expression of interest for those female profiles who want to work after marriage, for both ‘masculine’ and gender-neutral jobs. Lastly, female profiles working in ‘feminine’ occupations who want to work after marriage receive more interest than those open to not working after marriage. These results indicate that men prefer a partner who wants to continue working after marriage only in the scenario when they are employed in a ‘feminine’ occupation.

Robustness: The specifications above include extensive controls for potential suitors based on their caste category, age, height, profile manager (self-managed or managed by parents, relatives or friends), income, highest level of education attained, and a dummy for whether their income is lower than the corresponding female profile. However, there may still be a concern that there are omitted variables at the male suitor level. In Table 5, we include suitor fixed effects as an additional robustness check, but this does not change our previous conclusions. We find a 12.9% decrease in probability of receiving an expression of interest for a working female profile relative to the non-working female profiles. This result, as before, is driven by the profiles in Delhi where an employed female profile is 17.2% less likely to receive an expression of interest. Similarly, we re-estimate the effect of a woman's occupational choice on the probability of receiving interest from a male suitor and report these results in Table 6. Once more, the results are similar to the patterns reported earlier. Female profiles that were indicated as being employed in 'masculine' occupations are 3.2% less likely to receive interest compared to those engaged in 'feminine' occupations. This effect is again largely driven by female profiles posted in Delhi where women working in 'masculine' occupations receive 5.2% lower interest relative to those in 'feminine' occupations.

6 Heterogeneity

In this section, we examine the heterogeneity in our results by the caste of female profiles, given the variation in gender and social norms across castes discussed above. Table 7, Panel A, reports the differential effects on probability of receiving an expression of interest by a working female profile when compared to those not working for each caste group. The overall results are reported in column (1), and columns (2), (3) and (4) capture disaggregated estimates for Brahmin, Other high castes and SC female profiles, respectively. Panel A shows that the 14.5% lower interests seen for employed female profiles is a high caste phenomenon. It is driven largely by the lower interest in working profiles that are Brahmin (14.7% lower) and Other high castes (21.1% lower). On the other hand, the SC employed female profiles, do not experience any significant lower probability of receiving interest vis-a-vis their peers who are not working. The results by caste for Delhi and Bangalore are reported in Panels B and C, respectively. The results in Panel B for Delhi are consistent with this broader observed pattern for each caste group in Panel A. In Delhi, both Brahmin and Other high caste employed females face 23.8% and 24.6% lower probability of receiving interest, respectively, than their caste peers who are not working. These results by caste are consistent with the existing literature on cultural determinants and status concerns such as purity and honor for higher caste women, which also means they are less likely to be employed compared to lower caste women (Eswaran *et al.*, 2013; Mahajan & Ramaswami, 2017).

Further analysis shows that these preferences are driven by male suitors belonging to the same caste, given the high prevalence of within-caste marriages in Indian matrimony. In our data, 68% of the total expressions of interest sent by Brahmin men are towards Brahmin female profiles, 72% of total expressions of interest by Other high caste men are towards same caste or Brahmin females and 71% of overall expressions of interest by SC men are towards SC females. Hence, upper caste men are much more likely to show interest in upper caste women although a modest proportion of interests cross caste lines. We thus also examine the heterogeneity in our results by caste of the potential male suitor (Table 8, Panel A). These results are consistent with the main findings above. Employed female profiles are less likely to elicit interest from male suitors belonging to Brahmin and Other high castes in Delhi but not from SC male suitors.[25]

However, Table 7, Panel C shows that these caste patterns do not hold true for the city of Bangalore. Brahmin employed female profiles receive 11% higher interest compared to Brahmin female profiles who are not working. The level of interest in Other high caste employed profiles is not significantly different but SC females who are employed receive 16.8% lower interest than those not employed. However, when we examine the heterogeneity along the caste of the potential male suitor, we do not find any significant differences across the working status of female profiles for any caste in Bangalore (Table 8, Panel B). Given these results, we conclude that there is no significant heterogeneity in interest displayed by

[25] The platform does not provided aggregate caste categories and these categories for the male profiles were obtained based on fuzzy matching with detailed caste lists provided by the respective states.

working status of the female profiles across castes in the south.[26]

In the appendix, we conduct similar analyses across female caste profiles to estimate the interest from male suitors towards different caste-occupational types for women. We report the results in Appendix Table A.8. Panel A reports the overall results while Panel B and Panel C report the results for Delhi and Bangalore, respectively. The results show that women employed in 'masculine' occupations are less likely to receive interest in comparison to those in 'feminine' occupations for Other high caste profiles. However, for Brahmin and SC female profiles the nature of occupation does not seem to matter. Both Brahmin and Other high castes show a positive preference, as before, for women who are not working. These results hold for profiles in Delhi in Panel B. For Bangalore, in Panel C, we do not find any consistent differential behavior for high caste-occupation groups (columns (2) vs column (3)) among the employed female profiles. While Brahmin women in neutral and masculine occupations are penalized relative to those in feminine occupations, this is not the case for other high caste female profiles.

We further examine the results by caste of the male suitor as well in Appendix Table A.9. We find that while there is lower interest for female profiles working in 'masculine' or gender-neutral occupations in Delhi among the high caste male suitors, it is significant only for Other high caste category of male suitors. The results by caste of male suitors in Delhi lend support for the hypothesis that higher caste men show less inclination for women in 'masculine' occupations in the north.

7 Discussion

Our findings indicate that men prefer partners who do not work, and if they do work their preference is for women engaged in occupations that are 'feminine', i.e. have a high pro-

[26]Notably, existing literature also finds that SC are less marginalized when they form a larger share of the population (Anderson *et al.*, 2011). The Southern states of India have historically had a larger share of lower caste population (Mahajan & Ramaswami, 2017) which could lead to smaller differences in cultural norms between the two caste groups. In fact, for the Southern state of Karnataka Deshpande (2001) finds that overall disparity between the SCs and "others" is much smaller viz-a-viz other states.

portion of female employees. Higher castes and north Indian men are more likely to exhibit such preferences. We attribute these preferences to regressive gender norms, particularly the gendered allocation of time that places a disproportionate burden of home production on women and confines them within the home.

Could the lower interest received by working women, instead, be due to the possibility that women who work are more discerning about potential partners and hence, are more likely to reject interested male suitors? Past rejection faced by men who showed interest in a working female profile may dissuade them from future expressions of interest towards working women profiles on the platform. To check this channel, we restrict our sample to male profiles that are younger than the median age of male profiles on the platform, under the assumption that they are likely to have had fewer interactions with potential female partners. We find that these male profiles are also less likely to express an interest for a working female (Panel A, Appendix Table A.10), validating our findings above.

Is it possible that our results are driven by male suitors whose education levels or family incomes are lower or whose caste categories do not match that of the female profiles? To test this, we restrict our analysis to male suitors on the platform who match fictitious female profiles either on caste or have at least as much education and family income.[27] We find that working women face the interest penalty (Appendix Table A.10) even when their education levels and family incomes are at most that of the male profile and their caste matches that of the male profile.[28] These results indicate that our findings are not driven by poor 'quality' of male interest for working women. The observed penalty is also imposed by men who are

[27]There is assortative matching in the marriage market on education in India, with higher educated women marrying higher educated men. Also, in most married couples, men either have more or equal education as the woman (Afridi *et al.*, 2022b).

[28]We find that on average men with higher education and income express interest in female profiles employed in 'feminine' occupations vis-a-vis women who are not working (Appendix Table A.11). This is not surprising given that existing studies show prevalence of male breadwinner norm wherein a husband is expected to earn more than the wife (Bertrand *et al.*, 2015). However, women working in 'masculine' occupations receive interest from similar average education and income male suitors as women working in 'feminine' occupations. Thus, on average, the quality of male interests (proxied by male education and income) for women working in masculine occupations does not compensate for the lower probability of receiving an interest from a male suitor.

likely to be considered 'high quality' potential matches on education and family income for a female profile.

Finally, could our findings be due to parental preferences rather than prevailing social norms? More conservative social attitudes could be attributable to profiles managed by parents. Although it is possible that the profile manager (the person who created the profile, e.g. parent) is different from the individual who operates or searches on the platform (e.g. male suitor), we nonetheless examine the heterogeneity in the probability of receiving an interest by working status of the female profile from self-managed versus parent-managed male profiles. We observe no significant differences in our results across these profiles (Appendix Table A.12).

Note that while we highlight the gender differences between regions in India (north vs south) in time spent on domestic work, there could be other factors such as safety concerns stemming from spatial variation in incidence of crimes against women leading to differential attitudes towards women's work. Data from the National Crime Record Bureau shows that there were 217 reported incidents of assaults and rapes against women (per million women) in 2019 in North India while this figure was 176 for the South. Although these numbers are not vastly different between the two regions, households in the north may prefer women to not work due to higher threat to their safety when working outside the home.[29] This preference can also extend to female dominated occupations where women are less likely to interact with male colleagues. However, the fact that we find significantly lower interest of high caste men in working women in the north, indicates that women's safety cannot be the only channel explaining the observed patterns in our analyses.

To summarize, our results for the penalty faced by employed women in the marriage market can be explained by patriarchal norms that are more prevalent in north India and amongst the high caste, as discussed previously. Women who work, in general, and those who work in male dominated occupations, are expected to have less time to devote to domestic

[29] It would be worthwhile to mention here that reported incidents of violence against women is likely to be a noisy and imperfect measure of the true incidence of crimes against women.

chores, be sexually impure due to greater interaction with men at work or more physically mobile than allowed by existing gender norms. Hence, our analyses suggest that working women and those engaged in non-traditional occupations are penalised in the marriage market. While there may be alternative channels that further explain our findings, the analyses here underline the salience of patriarchal gender norms.

Can higher female education weaken regressive gender norms in a society? Two plausible mechanisms can be at play here – higher *home productivity* of educated women (Afridi *et al.*, 2022b) releasing their time from domestic work, and/or the *income effect* due to higher expected lifelong earnings with higher education.[30] Appendix Table A.13 reports the overall results for female profiles in column (1) and those by their stated education - Diploma, Bachelors (BA) and Masters (MA) - are reported in columns (2), (3) and (4), respectively. We find that the penalty on working women is marginally lower when they have BA or MA level of education vs Diploma, but these differences are not statistically significant. There is no significant penalty faced by working female profiles in Bangalore across education categories.[31]

Next, we examine heterogeneity in our results by the education level of male suitors. Higher education can possibly reduce the weight placed by men on adhering to gender regressive social norms. At the same time, men who are more educated are likely to be a select sample in terms of being socially more progressive. Appendix Table A.14, Panel A, reports the differential probability of interest towards working women by male suitors' education levels for both cities. The results for Delhi and Bangalore are reported in Panel B and Panel C, respectively. The overall results for men are reported in column (1), while columns (2), (3) and (4) report these for male suitors with Diploma, Bachelors (BA) and Masters (MA) education levels, respectively. The overall results in Panel A show that working

[30]While current income for fictitious female profiles is held constant across education levels in the experiment, future or expected income is likely to be higher for more educated women since returns to experience increase with education (Braga, 2018).

[31]we test for the difference in probability of receiving a male interest across education levels of female profiles and are unable to reject the null that the effects are equal. The results are omitted for brevity.

female profiles have a lower probability of receiving interest from male suitors with a Diploma and BA education. There is no differential effect for male suitors with an MA and the degree of penalty for employed women is lower from male suitors having BA (8.5%) vs Diploma (31%) levels of education. These results are valid for Delhi while Bangalore does not exhibit a significant negative penalty for working female profiles across education levels, as shown previously. The suggestive evidence here indicates that engaging with both genders, rather than women alone, may be relevant for attenuating regressive gender norms through educational interventions (e.g. Dhar *et al.* (2022)). In future research we hope to analyze how social norms around women's work can be weakened effectively through such interventions.

There are a few limitations and caveats to our findings, however. First, by design this study is restricted to one avenue of finding marriage matches - that of online matrimonial sites. These websites are more likely to have users who have above average literacy, access and comfort with the internet, and wealth and means, as we have shown above. However, this limitation to external validity is similar to other online and correspondence studies. We conduct an extensive list of heterogeneity analyses by education, caste, employment, type of work and location to address external validity issues. Our finding that less educated women are more likely to receive such a penalty and that less educated men are more likely to place the penalty on working women indicates that the marriage market penalty on working women may be higher in the population (in India) than on the platform itself.

Another limitation of this study is that of algorithmic exposure, inherent in many commercial online sites and services, which push content or suggestions at users. The potential differential exposure of certain types of profiles to male suitors was not in the control of this research study. However, our results give a true account of the gender bias in responses which would mimic users' experiences on the marriage website. Thus, irrespective of actual viewing of these profiles, our findings indicate the relative preferences of suitors on the marriage matching platform.[32]

[32] For instance, if a male profile indicates that only not-working women are wanted, they may never see a working female profile. This does not bias our analyses. In fact, not expressing an interest in a working

8 Conclusion

We conduct an online experiment that allows us to measure partner preferences of men on a digital marriage match-making platform in India. We find that women who are currently working are 14.5% less likely to receive interest from male suitors relative to women who are currently not working. Moreover, women engaged in 'masculine' occupations are 3.2% less likely to elicit interest compared to women employed in 'feminine' occupations. In addition, there is greater interest in women who would like to continue to work after marriage in a 'feminine' job, relative to women who would continue in a 'masculine' job.

These results are driven by responses in Delhi within high caste categories, highlighting the strong presence of patriarchal and regressive gender norms typically associated with north India and upper castes on preferences for female partner characteristics. Our findings suggest that expectations regarding returns in the marriage market may influence women's decisions about labor force participation before marriage and the nature of work they engage in, with implications for policy measures which attempt to close gender gaps in labor force participation and occupational sex segregation.

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female profile that we create allows one to capture such algorithmic behaviour.

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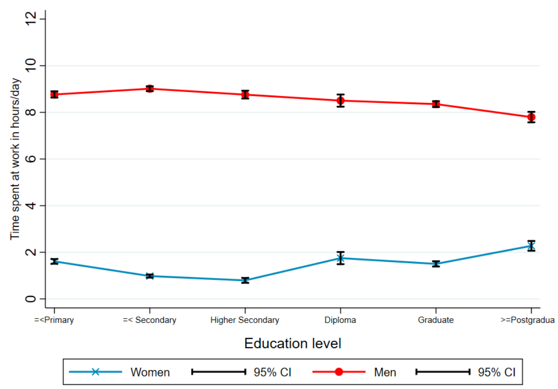
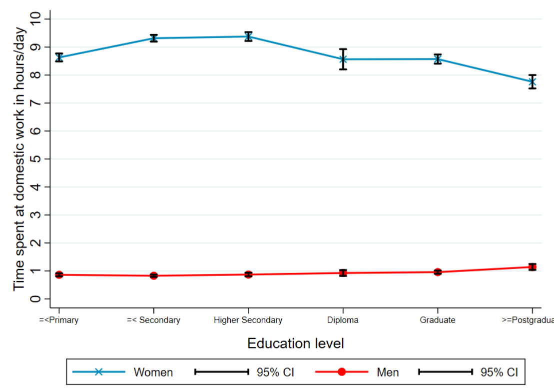
Figure 1: Time Spent in Domestic Work and in the Labor Market

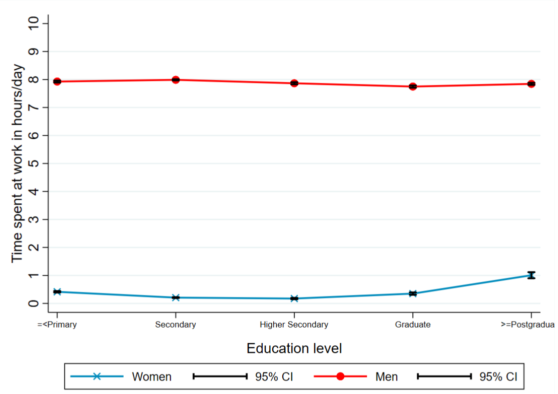
(a) Labor market (TUS)



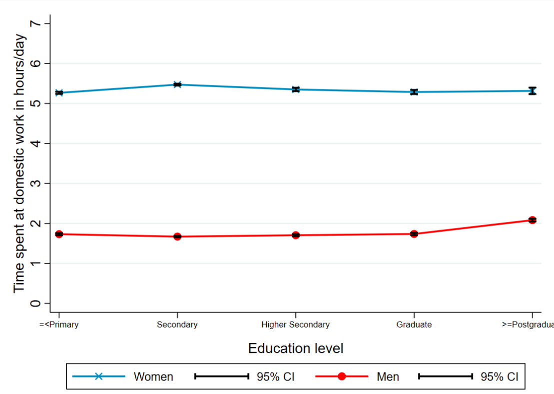
(b) Domestic work (TUS)



(c) Labor market (CPHS)



(d) Domestic work (CPHS)



Notes: Figures (a) and (c) plot the average time spent per day in the labor market by gender and education. Figures (b) and (d) plot the average time spent per day in domestic work (household chores) by gender and education. The sample includes urban married women and men aged 20-45 years.
Source: Time Use data (TUS) 2019 for Figures (a) and (b); 24th and 25th waves (September 2021 to April 2022) of the CMIE-CPHS, People of India dataset for Figures (c) and (d).

Figure 2: Female Profile Creation on the Platform

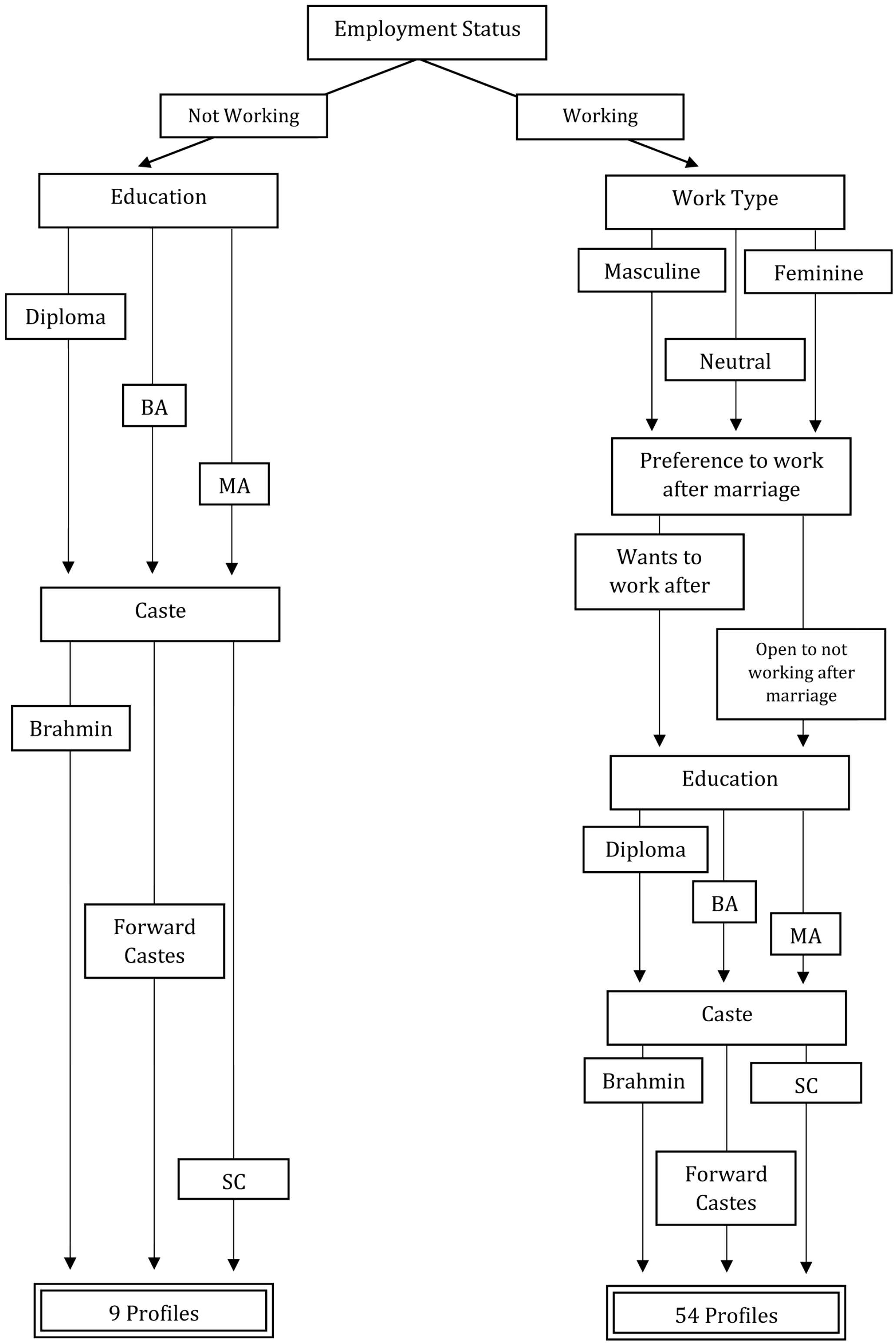


Table 1: Descriptive Statistics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Overall			Delhi			Bangalore		
	Mean	SD	N	Mean	SD	N	Mean	SD	N
All Profiles	6.24	24.18	375543	5.86	23.50	300006	7.71	26.68	75537
Work Status									
Not Working	6.94	25.42	53649	6.68	24.98	42858	7.97	27.08	10791
Working	6.12	23.97	321894	5.73	23.24	257148	7.67	26.61	64746
Work Type									
Feminine	6.18	24.09	107298	5.86	23.49	85716	7.47	26.30	21582
Masculine	6.00	23.75	107298	5.58	22.96	85716	7.65	26.59	21582
Neutral	6.17	24.06	107298	5.74	23.26	85716	7.88	26.94	21582
Prefers to work after marriage									
No	6.02	23.78	160947	5.61	23.01	128574	7.62	26.54	32373
Yes	6.22	24.15	160947	5.85	23.46	128574	7.71	26.68	32373
Caste									
Brahmin	6.67	24.94	125181	6.16	24.04	100002	8.67	28.14	25179
Other High Caste	6.94	25.42	125181	6.77	25.12	100002	7.62	26.53	25179
Scheduled Caste	5.10	22.00	125181	4.66	21.08	100002	6.84	25.25	25179
Highest Education Level									
Diploma	5.87	23.51	125181	5.58	22.96	100002	7.02	25.55	25179
Bachelor in Arts (BA)	6.30	24.29	125181	5.84	23.45	100002	8.12	27.32	25179
Masters in Arts (MA)	6.54	24.72	125181	6.17	24.07	100002	7.99	27.12	25179

Notes: The table shows the average proportion of male profiles that show an interest in our fictitious female profiles. The first row shows the overall proportion for all created profiles while the remaining rows show the proportion of interests by caste, education, employment and preference to work after marriage for the fictitious female profiles.

Table 2: Effect of Female Work Status on Male Interest

	(1)	(2)	(3)
	Overall	Delhi	Bangalore
Working	–0.009***	–0.010***	–0.002
	(0.001)	(0.002)	(0.004)
Constant	0.039	0.011	0.078
	(0.032)	(0.031)	(0.092)
Observations	329427	265545	63882
Mean Y	0.062	0.059	0.078
Controls			
Caste FE		✓	✓
City × Caste FE	✓		
Education FE	✓	✓	✓
Male profile controls	✓	✓	✓

Notes: The dependent variable is an indicator variable that takes a value of one if a fictitious female profile received an interest from a male profile and zero otherwise. The main explanatory variable, 'Working' is an indicator variable that takes a value of one for a fictitious female profile who is currently employed and zero otherwise. Controls include female profiles' education, caste category and city of residence; interacting male profile's highest level of education, age, height, caste category, profile manager (self/parent/managed by others), income and whether income is less than that of the corresponding fictitious female profile. Standard errors clustered at the level of the interacting male's (suitor) profile in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 3: Effect of Female Occupation Type on Male Interest

	(1)	(2)	(3)
	Overall	Delhi	Bangalore
Not working	0.008***	0.009***	0.004
	(0.002)	(0.002)	(0.004)
Working - Neutral	–0.000	–0.001	0.004*
	(0.001)	(0.001)	(0.002)
Working - Masculine	–0.002**	–0.003***	0.002
	(0.001)	(0.001)	(0.002)
Constant	0.032	0.002	0.074
	(0.032)	(0.031)	(0.092)
Observations	329427	265545	63882
Mean Y	0.062	0.059	0.078
Masculine=Neutral	0.057	0.104	0.316
Controls			
Caste FE		✓	✓
City × Caste FE	✓		
Education FE	✓	✓	✓
Male profile controls	✓	✓	✓

Notes: The dependent variable is an indicator variable that takes a value of one if a fictitious female profile received an interest from a male profile and zero otherwise. The explanatory variable, 'Not working' is an indicator variable that takes a value of one for a fictitious female profile who is currently not employed and zero otherwise; 'Masculine' takes a value one if a fictitious female profile is engaged in a masculine occupation and zero otherwise; 'Neutral' takes a value of one if a fictitious female profile is engaged in a gender neutral occupation and zero otherwise. The reference group for occupation type is female profiles engaged in feminine occupations. Details on occupational classification based on gender distribution are discussed in section 3. Controls include female profiles' education, caste category and city of residence; interacting male profile's highest level of education, age, height, caste category, profile manager (self/parent/managed by others), income and whether income is less than that of the corresponding fictitious female profile. Standard errors clustered at the level of the interacting male's (suitor) profile in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 4: Effect of Female Occupation Type and Work Preference after Marriage on Male Interest

	(1)	(2)	(3)
	Overall	Delhi	Bangalore
Working - Neutral	0.003***	0.004***	0.002
	(0.001)	(0.001)	(0.003)
Working - Masculine	0.002	0.001	0.004
	(0.001)	(0.001)	(0.003)
Work after Marriage	0.007***	0.008***	0.002
	(0.001)	(0.001)	(0.003)
Neutral x Work after Marriage	–0.007***	–0.010***	0.004
	(0.002)	(0.002)	(0.004)
Masculine x Work after Marriage	–0.007***	–0.008***	–0.006
	(0.002)	(0.002)	(0.004)
Constant	0.036	0.004	0.072
	(0.032)	(0.031)	(0.092)
Observations	282366	227610	54756
Mean Y	0.061	0.057	0.077
Masculine = Masculine x Work after Marriage	0.002	0.006	0.132
Neutral = Neutral x Work after Marriage	0.000	0.000	0.819
Controls			
Caste FE		✓	✓
City × Caste FE	✓		
Education FE	✓	✓	✓
Male profile controls	✓	✓	✓

Notes: The sample consists of fictitious employed female profiles. The dependent variable is an indicator variable that takes a value of one if a fictitious female profile received an interest from a male profile and zero otherwise. The explanatory variable, 'Masculine' takes a value of one if a fictitious female profile is engaged in a masculine occupation and zero otherwise; 'Neutral' takes a value of one if a fictitious female profile is engaged in a gender neutral occupation and zero otherwise. The reference group for occupation type is fictitious female profiles engaged in feminine occupations. Details on occupational classification based on gender distribution are discussed in section 3. 'Work after marriage' takes value one if the profile description mentions that the woman prefers to work after marriage and zero otherwise. Controls include female profiles' education, caste category and city of residence; interacting male profile's highest level of education, age, height, caste category, profile manager (self/parent/managed by others), income and whether income is less than that of the corresponding fictitious female profile. Standard errors clustered at the level of the interacting male's (suitor) profile in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 5: Effect of Female Work Status on Male Interest: Robustness

	(1)	(2)	(3)
	Overall	Delhi	Bangalore
Working	–0.008***	–0.010***	–0.002
	(0.001)	(0.002)	(0.004)
Constant	0.102***	0.071***	0.094***
	(0.011)	(0.002)	(0.004)
Observations	338058	272916	65142
Mean Y	0.062	0.058	0.077
Controls			
Caste FE		✓	✓
City × Caste FE	✓		
Education FE	✓	✓	✓
Male Profile FE	✓	✓	✓

Notes: The dependent variable is an indicator variable that takes a value of one if a fictitious female profile received an interest from a male profile and zero otherwise. The main explanatory variable, 'Working' is an indicator variable that takes a value of one for a female profile who is currently employed and zero otherwise. Controls include female profiles' education, caste category and city of residence. All regressions control for fixed effects for the engaging male profiles. Standard errors clustered at the level of the interacting male's (suitor) profile in parentheses. *** p<0.01, ** p<0.05, * emphp<0.1.

Table 6: Effect of Female Occupation Type on Male Interest: Robustness

	(1)	(2)	(3)
	Overall	Delhi	Bangalore
Not working	0.008***	0.009***	0.003
	(0.002)	(0.002)	(0.004)
Working - Neutral	–0.000	–0.001	0.003
	(0.001)	(0.001)	(0.002)
Working - Masculine	–0.002**	–0.003***	0.001
	(0.001)	(0.001)	(0.002)
Constant	0.095***	0.062***	0.091***
	(0.011)	(0.001)	(0.004)
Observations	338058	272916	65142
Mean Y	0.062	0.058	0.077
Masculine=Neutral	0.061	0.101	0.367
Controls			
Caste FE		✓	✓
City × Caste FE	✓		
Education FE	✓	✓	✓
Male Profile FE	✓	✓	✓

Notes: The dependent variable is an indicator variable that takes a value of one if a fictitious female profile received an interest from a male profile and zero otherwise. The explanatory variable, 'Not working' is an indicator variable that takes a value of one for a fictitious female profile who is currently not employed and zero otherwise; 'Masculine' takes a value of one if a fictitious female profile is engaged in a masculine occupation and zero otherwise; 'Neutral' takes a value of one if a fictitious female profile is engaged in a gender neutral occupation and zero otherwise. The reference group for occupation type is females profiles engaged in feminine occupations. Details on occupational classification based on gender distribution are discussed in section 3. Controls include female profiles' education, caste category and city of residence. All regressions control for fixed effects for the engaging male profiles. Standard errors clustered at the level of the interacting male's (suitor) profile in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 7: Effect of Female Work Status on Male Interest (by Caste of Female Profile)

	(1)	(2)	(3)	(4)
	Overall	Brahmin	Other High Castes	Scheduled Caste
Panel A : Overall				
Working	–0.009***	–0.010***	–0.015***	–0.001
	(0.001)	(0.002)	(0.002)	(0.002)
Observations	329427	109809	109809	109809
Mean Y	0.062	0.068	0.071	0.048
City FE		✓	✓	✓
City × Caste FE	✓			
Education FE	✓	✓	✓	✓
Male profile controls	✓	✓	✓	✓
Panel B : Delhi				
Working	–0.010***	–0.015***	–0.017***	0.001
	(0.002)	(0.003)	(0.003)	(0.002)
Observations	265545	88515	88515	88515
Mean Y	0.0586	0.0629	0.0690	0.0439
Panel C : Bangalore				
Working	–0.002	0.010*	–0.005	–0.011**
	(0.004)	(0.005)	(0.005)	(0.006)
Observations	63882	21294	21294	21294
Mean Y	0.0776	0.0902	0.0775	0.0651
Caste FE	✓			
Education FE	✓	✓	✓	✓
Male profile controls	✓	✓	✓	✓

Notes: The dependent variable is an indicator variable that takes a value of one if a fictitious female profile received an interest from a male profile and zero otherwise. The main explanatory variable, 'Working' is an indicator variable that takes a value of one for a fictitious female profile who is currently employed and zero otherwise. Column (1) shows the overall effect while columns (2)-(4) show the effect by the caste of the fictitious female profile. Controls include female profiles' education, caste category and city of residence; interacting male profile's highest level of education, age, height, caste category, profile manager (self/parent/managed by others), income and whether income is less than that of the corresponding fictitious female profile. Standard errors clustered at the level of the interacting male's (suitor) profile in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

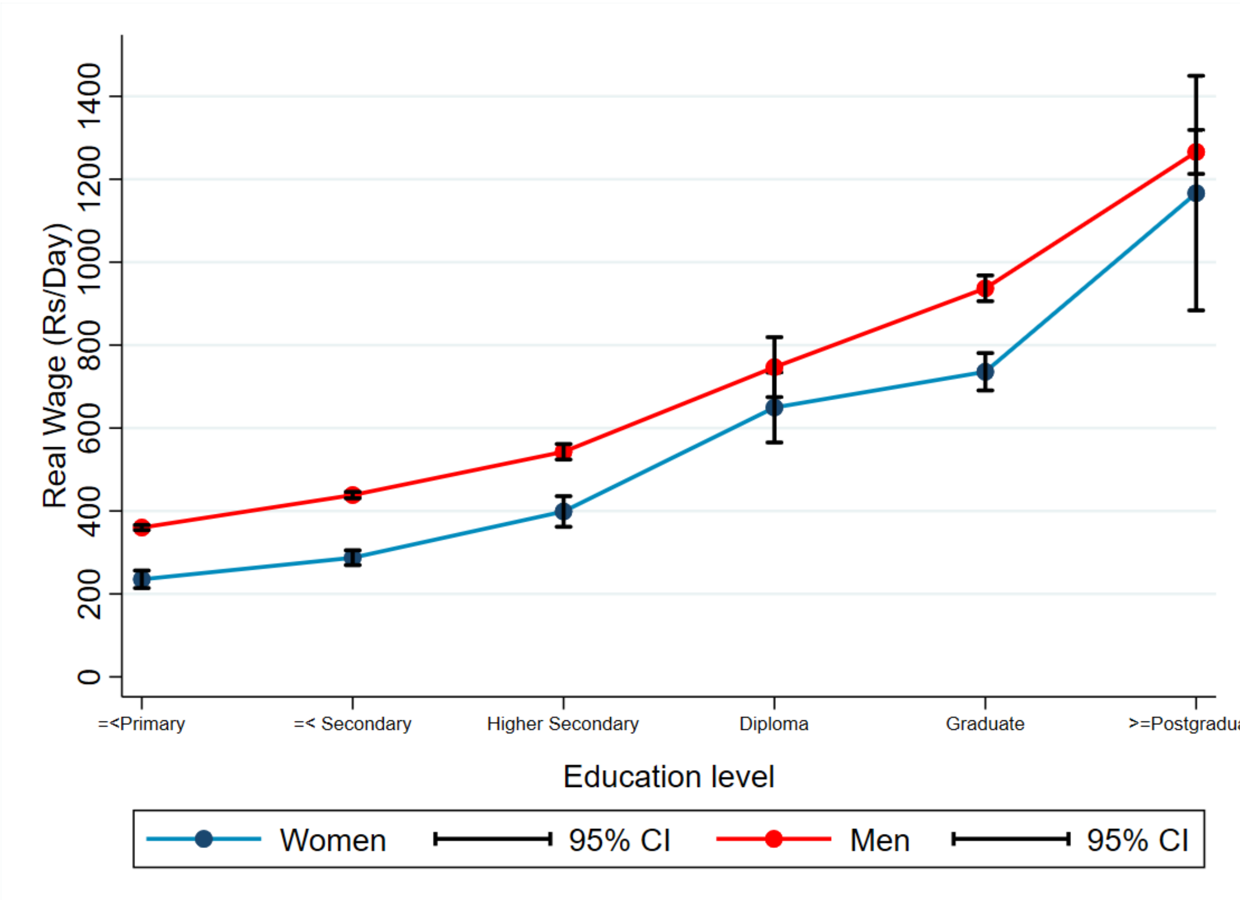
Table 8: Effect of Female Work Status on Male Interest (by Caste of the Interacting Male)

	(1)	(2)	(3)	(4)
	Overall	Brahmin	Other High Castes	Scheduled Caste
Panel A : Overall				
Working	–0.009***	–0.010***	–0.010***	0.004
	(0.001)	(0.003)	(0.002)	(0.004)
Observations	329427	75159	225351	28917
Mean Y	0.0623	0.0577	0.0650	0.0532
City × Caste FE	✓	✓	✓	✓
Education FE	✓	✓	✓	✓
Male profile controls	✓	✓	✓	✓
Panel B : Delhi				
Working	–0.010***	–0.013***	–0.011***	0.005
	(0.002)	(0.003)	(0.002)	(0.005)
Observations	265545	62937	179676	22932
Mean Y	0.0586	0.0557	0.0603	0.0531
Panel C : Bangalore				
Working	–0.002	0.005	–0.004	0.002
	(0.004)	(0.007)	(0.004)	(0.011)
Observations	63882	12222	45675	5985
Mean Y	0.0776	0.0676	0.0834	0.0535
Caste FE	✓	✓	✓	✓
Education FE	✓	✓	✓	✓
Male profile controls	✓	✓	✓	✓

Notes: The dependent variable is an indicator variable that takes a value of one if a fictitious female profile received an interest from a male profile and zero otherwise. The main explanatory variable, 'Working' is an indicator variable that takes a value of one for a fictitious female profile who is currently employed and zero otherwise. Column (1) shows the overall effect while columns (2)-(4) show the effect by the caste of the interacting male profile. Controls include female profiles' education, caste category and city of residence; interacting male profile's highest level of education, age, height, caste category, profile manager (self/parent/managed by others), income and whether income is less than that of the corresponding fictitious female profile. Standard errors clustered at the level of the interacting male's (suitor) profile in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

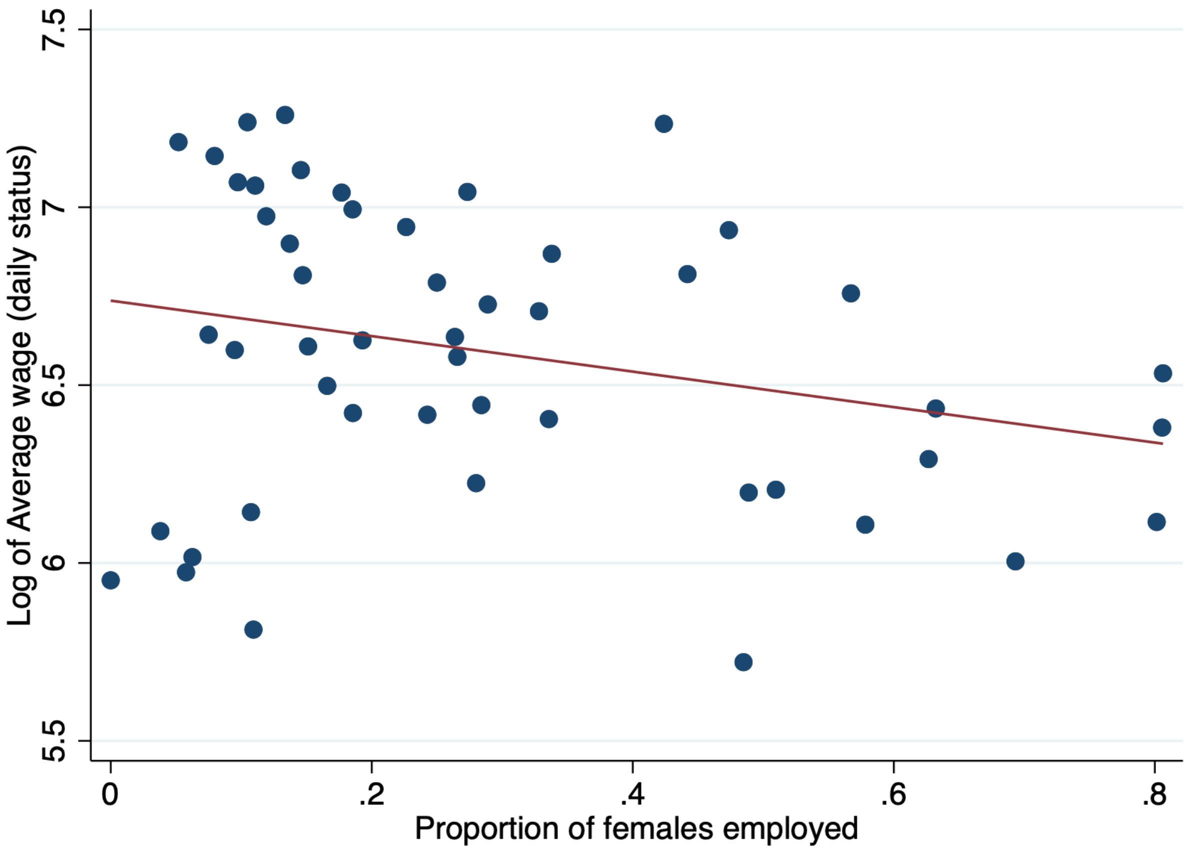
A Online Appendix

Figure A.1: Returns to Education by Gender



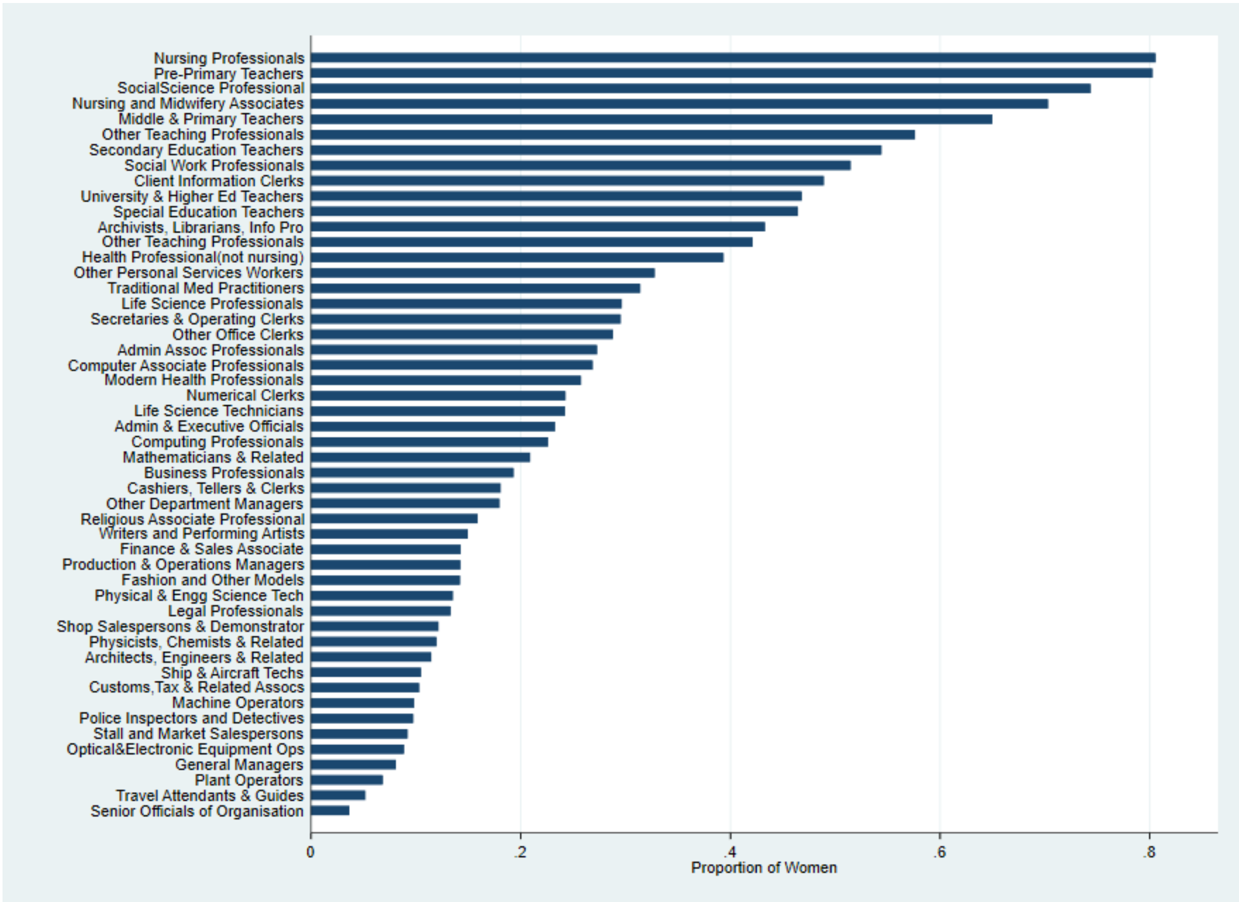
Notes: The figure plots average daily wage rates for employed individuals in paid employment (salaried or casual) by gender and education. The sample includes individuals aged 20-45 years in urban India.
Source: Periodic labor Force Survey, 2018-19

Figure A.2: Occupational Wage by Proportion of Women Workers



Notes: The figure shows the correlation between the proportion of women workers of the total employees in an occupation (X-axis) and the log of the average daily wage in each occupation (Y-axis) in urban India. The selected occupations are those where at least 50% of the total workers have completed schooling.
Source: Periodic Labor Force Survey, 2018-19.

Figure A.3: Women's Occupational Distribution



Notes: The figure shows the proportion of women employed for each occupation. The occupations are chosen where at least 50% of the total workers have completed schooling.
Source: Periodic Labor Force Survey, 2018-19

Table A.1: Time Spent on Domestic Work by Women

	All Education		Atleast Completed Schooling	
	(1)	(2)	(3)	(4)
Working	–0.645***	–0.664***	–0.736***	–0.733***
	(0.021)	(0.021)	(0.038)	(0.039)
Constant	0.760***	0.780***	–0.066	0.205
	(0.131)	(0.129)	(0.249)	(0.255)
Observations	103597	103597	28343	28343
Mean Y	5.373	5.373	5.325	5.325
Controls				
State FE	✓		✓	
District FE		✓		✓
Other Controls	✓	✓	✓	✓

Notes: The dependent variable is the log of time spent on domestic work. For zero time spent we add a small value of 0.001 and then take the log transformation. 'Working' is an indicator variable that takes a value of one for women who are currently employed, and zero otherwise. Controls include age, age squared, education, caste, religion, wave number, household monthly per capita expenditure (MPCE) decile and number of children aged between 0 to 5 years. Each column reports the effective number of observations after incorporating the included fixed effects. Regressions are weighted using the provided survey weights for each wave. Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.
Source: 24th and 25th wave of the CMIE CPHS, People of India from September 2021 to April 2022. The sample includes urban married women aged 20-45.

Table A.2: Time Spent on Domestic Work by Women

	All Education		Atleast Completed Schooling	
	(1)	(2)	(3)	(4)
Not Working	0.500***	0.518***	0.636***	0.625***
	(0.019)	(0.019)	(0.031)	(0.032)
Working - Neutral	–0.182***	–0.170***	–0.096	–0.123*
	(0.035)	(0.035)	(0.069)	(0.070)
Working - Masculine	–0.594***	–0.605***	–0.521***	–0.524***
	(0.087)	(0.087)	(0.194)	(0.196)
Constant	0.315**	0.305**	–0.707***	–0.423*
	(0.133)	(0.132)	(0.249)	(0.254)
Observations	103597	103597	28343	28343
Controls				
State FE	✓		✓	
District FE		✓		✓
Other Controls	✓	✓	✓	✓

Notes: The dependent variable is the log of time spent on domestic work. For zero time spent we add a small value of 0.001 and then take the log transformation. Not Working indicates a woman who is currently not employed. Neutral indicates a woman employed in a gender neutral occupation (proportion of female employees between 4 to 10%). Masculine indicates a woman employed in a masculine occupation (proportion of female employees less than 4%). The reference category is women employed in feminine occupations (proportion of female employees more than 10%). These cutoffs for stereotypical gendered occupations are arrived by using the distribution of female vs male workers in a given occupation. We take the occupations at ≈ 70th percentile or above of the distribution of female workers as female dominated and 35th percentile or below as male dominated. Controls include age, age squared, education, caste, religion, wave number, household MPCE decile and number of children aged between 0 to 5 years. Each column reports the effective number of observations after incorporating the included fixed effects. Regressions are weighted using the provided survey weights for each wave. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
Source: 24th and 25th wave of the CMIE CPHS, People of India dataset, September 2021 to April 2022. The sample includes urban married women aged 20-45.

Table A.3: Gender Gap in Domestic Work and Market Time: by Region

Sample	All Education		Atleast Completed Schooling	
	Domestic	Market	Domestic	Market
Female	5.571***	–5.819***	5.348***	–5.760***
	(0.044)	(0.054)	(0.066)	(0.084)
North	–0.498***	–0.010	–0.615***	–0.030
	(0.058)	(0.047)	(0.087)	(0.077)
Female × North	0.507***	–0.840***	0.609***	–0.583***
	(0.059)	(0.069)	(0.091)	(0.110)
Constant	–7.173***	–3.182***	–6.488***	–5.457***
	(0.331)	(0.458)	(0.565)	(0.772)
Observations	46462	46458	20121	20121
Other Controls	✓	✓	✓	✓

Notes: The dependent variable is the log of daily time spent on domestic work for the first and third specification, and the log of daily time spent at work for the second and fourth specification. For zero time spent we add a small value of 0.001 and then take the log transformation. 'Female' is an indicator that takes value one for women, and 0 for men. The northern states include Gujarat, Rajasthan, Uttar Pradesh, Madhya Pradesh, Punjab, Haryana, and Delhi. The southern states include Kerala, Tamil Nadu, Andhra Pradesh, Telangana, Karnataka, and Maharashtra. Controls include age, age squared, education, caste, religion, household MPCE decile and number of children aged between 0 to 5 years. In these specifications we do not control for state or district fixed effects since the main objective is to examine regional differences. Regressions are weighted using the provided survey weights. Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.
Source: Time Use Survey (2019) across all states of India. The sample includes urban married women aged 20-45.

Table A.4: Gender Gap in Domestic Work and Market Time: by Caste

Sample	All Education		Atleast Completed Schooling	
	Domestic	Market	Domestic	Market
Female	5.582***	–6.193***	5.220***	–6.006***
	(0.056)	(0.064)	(0.099)	(0.119)
High Caste	–0.177***	0.032	–0.322***	0.056
	(0.062)	(0.047)	(0.104)	(0.084)
Female × High Caste	0.159**	–0.208***	0.308***	–0.106
	(0.063)	(0.072)	(0.107)	(0.128)
Constant	–6.892***	–2.773***	–6.089***	–5.331***
	(0.292)	(0.394)	(0.507)	(0.680)
Observations	63964	64058	27248	27301
State FE	✓	✓	✓	✓
Other Controls	✓	✓	✓	✓

Notes: The dependent variable is the log of daily time spent on domestic work for the first and third specification, and the log of daily time spent at work for the second and fourth specification. For zero time spent we add a small value of 0.001 and then take the log transformation. 'Female' is an indicator that takes value one for women, and 0 for men. Higher Caste is an indicator that takes value 1 if the person belongs to Other Backward Classes or Other Highe Castes and zero otherwise. Controls include age, age squared, education, caste, religion, household MPCE decile and number of children aged between 0 to 5 years. Each column reports the effective number of observations after incorporating the included fixed effects. Regressions are weighted using the provided survey weights. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
Source: Time Use Survey (2019) across all states of India. The sample includes urban married women aged 20-45.

Table A.5: Marriage Platform and Population Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
		PLFS			Platform	
	Delhi	Karnataka	Overall	Delhi	Karnataka	Overall
Panel A : Men						
Personal Characteristics						
Age	25.202	25.951	25.586	30.426	30.999	30.552
Scheduled Caste/Tribe	0.231	0.149	0.189	0.072	0.051	0.067
Annual Income ('00000 INR)	3.194	2.613	2.807	12.128	15.345	12.843
Highest Level of Education						
High School/Diploma	0.275	0.342	0.309	0.070	0.056	0.067
Graduate	0.626	0.453	0.537	0.530	0.583	0.542
Postgraduate	0.100	0.205	0.154	0.400	0.361	0.391
N	224	361	585	39329	11132	50461
Panel B : Women						
Personal Characteristics						
Age	23.030	22.979	23.005	29.526	29.386	29.501
Scheduled Caste/Tribe	0.200	0.162	0.181	0.087	0.049	0.080
Annual Income ('00000 INR)	3.089	2.613	2.816	7.521	10.239	8.065
Highest Level of Education						
High School/Diploma	0.331	0.492	0.410	0.035	0.015	0.031
Graduate	0.470	0.451	0.461	0.416	0.531	0.437
Postgraduate	0.199	0.057	0.129	0.550	0.454	0.532
N	158	245	403	39054	8557	47611

Notes: The statistics from the PLFS 2018-18 are in columns (1)-(3) after keeping never married individuals who have at least completed schooling in urban Delhi-NCR and Karnataka. Average age and low caste proportion is obtained for this sample of individuals. Annual income is calculated for the subset of men and women in this sample who report working in the labor market (includes paid work and self-employment). The statistics for profiles obtained from the marriage portal in September 2020 are in columns (4)-(6). Again, we keep never married individuals on the platform. The income is calculated by taking the mid point of the range of income value reported in a profile on the portal. The average income is only calculated for profiles that declare an income, i.e. among the working men and women who report income. The *jati* was matched with state caste lists to classify the scraped profiles from the platform as Scheduled Caste.

Table A.6: Profile Characteristics: by Gender

	Overall		Female		Male	
	Mean	SD	Mean	SD	Mean	SD
Personal Characteristics						
Age (Years)	30.612	5.511	29.907	4.986	31.059	5.775
Height (Inches)	64.635	3.670	62.734	3.086	65.838	3.497
Income ('00000 INR)	10.427	16.781	7.763	13.050	12.113	18.567
Caste Category						
Brahmin	0.194	0.395	0.200	0.400	0.190	0.392
Other High Castes	0.750	0.433	0.742	0.437	0.754	0.431
SC/ST	0.057	0.231	0.058	0.234	0.056	0.230
Profile Manager						
Managed by Parents/Relative	0.405	0.491	0.581	0.493	0.294	0.456
Managed by Self	0.589	0.492	0.415	0.493	0.700	0.458
Managed by Others	0.005	0.073	0.004	0.063	0.006	0.078
Highest Level of Education						
High School/Diploma	0.086	0.281	0.039	0.194	0.116	0.320
Bachelors	0.479	0.500	0.427	0.495	0.512	0.500
Masters	0.362	0.481	0.455	0.498	0.304	0.460
Professional Degree	0.021	0.142	0.026	0.160	0.017	0.129
M.Phil. PhD	0.017	0.128	0.023	0.151	0.013	0.111
Other degree	0.035	0.184	0.029	0.167	0.039	0.194
Observations	407545		157959		249586	

Notes: The table reports the average characteristics for male and female profiles active on the platform in September 2020. Income is calculated by taking the mid point of the range of income value declared by the male on the portal. For unemployed males the income is zero. The caste group is assigned based on the aggregate caste or detailed caste category. The *jati* was matched with state caste lists to classify profiles as Scheduled Caste.

Table A.7: Engaging Male Profile Characteristics

	Overall		Delhi		Bangalore	
	Mean	SD	Mean	SD	Mean	SD
Personal Characteristics						
Age (Years)	29.151	3.122	28.973	3.087	30.164	3.177
Height (Inches)	65.985	3.408	65.965	3.418	66.057	3.367
Income ('00000 INR)	9.078	12.750	8.872	12.240	9.849	13.987
Caste Category						
Brahmin	0.227	0.419	0.236	0.424	0.191	0.393
Other High Castes	0.683	0.465	0.676	0.468	0.714	0.452
SC/ST	0.091	0.287	0.088	0.283	0.095	0.294
Profile Manager						
Managed by Parents/Relative	0.291	0.454	0.305	0.460	0.210	0.407
Managed by himself	0.702	0.458	0.687	0.464	0.782	0.413
Managed by Others	0.008	0.088	0.008	0.088	0.008	0.088
Highest Level of Education						
High School/Diploma	0.146	0.354	0.143	0.350	0.171	0.377
Bachelors	0.526	0.499	0.530	0.499	0.492	0.500
Masters	0.261	0.439	0.264	0.441	0.255	0.436
Professional Degree	0.014	0.116	0.014	0.117	0.012	0.108
M.Phil. PhD	0.007	0.083	0.006	0.080	0.010	0.099
Other degree	0.046	0.209	0.043	0.202	0.060	0.238
Observations	5013		4217		1016	

Notes: The table reports the average characteristics for male profiles on the platform that showed interest in the fictitious female profiles uploaded on the platform. Income is calculated by taking the mid point of the range of income value declared by the male on the portal. For unemployed males the income is zero. The caste group is assigned based on the aggregate caste or detailed caste category. The *jati* was matched with state caste lists to classify profiles as Scheduled Caste.

Table A.8: Effect of Female Occupation Type on Male Interest (by Female Caste)

	(1)	(2)	(3)	(4)
	Overall	Brahmin	Other High castes	Scheduled castes
Panel A : Overall				
Not working	0.008***	0.009***	0.014***	0.001
	(0.002)	(0.003)	(0.003)	(0.002)
Working - Neutral	–0.000	–0.004**	0.003	0.001
	(0.001)	(0.002)	(0.002)	(0.001)
Working - Masculine	–0.002**	0.001	–0.005***	–0.002
	(0.001)	(0.002)	(0.002)	(0.001)
Observations	329427	109809	109809	109809
Mean Y	0.0623	0.0682	0.0707	0.0480
City FE		✓	✓	✓
City × Caste FE	✓			
Education FE	✓	✓	✓	✓
Male profile controls	✓	✓	✓	✓
Panel B : Delhi				
Not working	0.009***	0.015***	0.015***	–0.003
	(0.002)	(0.003)	(0.003)	(0.002)
Working - Neutral	–0.001	–0.003*	–0.000	–0.001
	(0.001)	(0.002)	(0.002)	(0.002)
Working - Masculine	–0.003***	0.002	–0.008***	–0.003**
	(0.001)	(0.002)	(0.002)	(0.002)
Observations	265545	88515	88515	88515
Mean Y	0.0586	0.0629	0.0690	0.0439
Panel C : Bangalore				
Not working	0.004	–0.016***	0.013**	0.014**
	(0.004)	(0.006)	(0.006)	(0.006)
Working - Neutral	0.004*	–0.008*	0.014***	0.006*
	(0.002)	(0.004)	(0.004)	(0.004)
Working - Masculine	0.002	–0.007*	0.011***	0.001
	(0.002)	(0.004)	(0.003)	(0.003)
Observations	63882	21294	21294	21294
Mean Y	0.0776	0.0902	0.0775	0.0651
Caste FE	✓			
Education FE	✓	✓	✓	✓
Male profile controls	✓	✓	✓	✓

Notes: The dependent variable is an indicator variable that takes a value of one if a fictitious female profile received an interest from a male profile and zero otherwise. The explanatory variable, 'Not working' is an indicator variable that takes a value of one for a fictitious female profile who is not currently employed and zero otherwise; 'Masculine' takes a value of one if a fictitious female profile is engaged in a masculine occupation and zero otherwise; 'Neutral' takes a value of one if a fictitious female profile is engaged in a gender neutral occupation and zero otherwise. The reference group for occupation type is females profiles engaged in feminine occupations. Details on occupational classification based on gender distribution are discussed in section 3. Column (1) shows the overall effect while columns (2)-(4) show the effect by the caste of the female profile. Controls include female profiles' education, caste category and city of residence; interacting male profile's highest level of education, age, height, caste category, profile manager (self/parent/managed by others), income and whether income is less than that of the corresponding fictitious female profile. Standard errors clustered at the level of the interacting male's (suitor) profile in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A.9: Effect of Female Occupation Type on Male Interest (by Caste of the Interacting Male)

	(1)	(2)	(3)	(4)
	Overall	Brahmin	Other High castes	SC
Panel A : Overall				
Not working	0.008***	0.008***	0.009***	–0.003
	(0.002)	(0.003)	(0.002)	(0.005)
Working - Neutral	–0.000	–0.001	–0.001	0.005*
	(0.001)	(0.002)	(0.001)	(0.003)
Working - Masculine	–0.002**	–0.003	–0.002*	–0.001
	(0.001)	(0.002)	(0.001)	(0.003)
Observations	329427	75159	225351	28917
Mean Y	0.062	0.058	0.065	0.053
City × Caste FE	✓	✓	✓	✓
Education FE	✓	✓	✓	✓
Male profile controls	✓	✓	✓	✓
Panel B : Delhi				
Not working	0.009***	0.011***	0.010***	–0.005
	(0.002)	(0.003)	(0.002)	(0.005)
Working - Neutral	–0.001	–0.001	–0.002	0.003
	(0.001)	(0.002)	(0.001)	(0.003)
Working - Masculine	–0.003***	–0.003	–0.003**	–0.002
	(0.001)	(0.002)	(0.001)	(0.003)
Observations	265545	62937	179676	22932
Mean Y	0.059	0.056	0.060	0.053
Panel C : Bangalore				
Not working	0.004	–0.006	0.006	0.004
	(0.004)	(0.007)	(0.005)	(0.011)
Working - Neutral	0.004*	–0.003	0.005*	0.013**
	(0.002)	(0.006)	(0.003)	(0.006)
Working - Masculine	0.002	–0.002	0.002	0.005
	(0.002)	(0.005)	(0.002)	(0.005)
Observations	63882	12222	45675	5985
Mean Y	0.078	0.068	0.083	0.053
Caste FE	✓	✓	✓	✓
Education FE	✓	✓	✓	✓
Male profile controls	✓	✓	✓	✓

Notes: The dependent variable is an indicator variable that takes a value of one if a fictitious female profile received an interest from a male profile and zero otherwise. The explanatory variable, 'Not working' is an indicator variable that takes a value of one for a fictitious female profile who is not currently employed and zero otherwise; 'Working - Masculine' takes a value of one if a fictitious female profile is engaged in a Masculine occupation and zero otherwise; 'Working - Neutral' takes a value of one if a fictitious female profile is engaged in a gender Neutral occupation and zero otherwise. The reference group for occupation type is females profiles engaged in Feminine occupations. Details on occupational classification based on gender distribution are discussed in section 3. Column (1) shows the overall effect while columns (2)-(4) show the effect by the caste of the female profile. Controls include female profiles' education, caste category and city of residence; interacting male profile's highest level of education, age, height, caste category, profile manager (self/parent/managed by others), income and whether income is less than that of the corresponding fictitious female profile. Standard errors clustered at the level of the interacting male's (suitor) profile in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.10: Effect of Female Work Status on Male Interest - Robustness by characteristics of Male Suitors

	(1)	(2)	(3)
	Overall	Delhi	Bangalore
Panel A : Male suitors lower than median male age			
Working	–0.006***	–0.007***	–0.001
	(0.002)	(0.002)	(0.005)
Observations	209286	183330	25956
Mean Y	0.056	0.054	0.070
Panel B : Male suitors matched on caste of female			
Working	–0.020***	–0.025***	–0.000
	(0.003)	(0.003)	(0.007)
Observations	100170	80871	19299
Mean Y	0.101	0.099	0.107
Panel C : Male suitors matched on education of female			
Working	–0.005***	–0.007***	0.003
	(0.002)	(0.002)	(0.004)
Observations	224175	181923	42252
Mean Y	0.063	0.059	0.078
Panel D : Male suitors matched on family income of female			
Working	–0.004**	–0.006***	0.004
	(0.002)	(0.002)	(0.004)
Observations	257103	205632	51471
Mean Y	0.066	0.063	0.079
Controls			
Caste FE		✓	✓
City × Caste FE	✓		
Education FE	✓	✓	✓
Male profile controls	✓	✓	✓

Notes: The dependent variable is an indicator variable that takes a value of one if a fictitious female profile received an interest from a male profile and zero otherwise. Panel A keeps the male profiles that have lower age than a median male profile on the platform, Panel B keeps set of male profiles to those that match the fictitious female profile on caste, Panel C keeps the set of male profiles that have at least as much education as the fictitious female profile and Panel D keeps the set of male profiles that have as much household income as the fictitious female profile. The main explanatory variable , 'Working' is an indicator variable that takes a value of one for a fictitious female profile who is currently employed and zero otherwise. Controls include female profiles' education, caste category and city of residence; interacting male profile's highest level of education, age, height, caste category, profile manager (self/parent/managed by others), income and whether income is less than that of the corresponding fictitious female profile. Standard errors clustered at the level of the interacting male's (suitor) profile in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A.11: Income and Education of Male Profiles that Express Interest in Fictitious Female Profile (by Working Status and Occupation of Female Profile)

	(1)	(2)	(3)
	Overall	Delhi	Bangalore
Panel A: Log income of the male suitor			
Not working	–0.119***	–0.115***	–0.139***
	(0.020)	(0.023)	(0.041)
Working - Neutral	0.049***	0.044**	0.064*
	(0.017)	(0.020)	(0.033)
Working - Masculine	0.008	–0.007	0.053
	(0.017)	(0.020)	(0.034)
Constant	1.923***	1.777***	1.901***
	(0.025)	(0.021)	(0.033)
Observations	20524	15567	4957
Mean Y	1.800	1.797	1.807
Panel B: Highest Level of Education of the male suitor			
Not working	–0.089***	–0.097***	–0.061*
	(0.015)	(0.017)	(0.034)
Working - Neutral	0.038***	0.046***	0.012
	(0.013)	(0.014)	(0.028)
Working - Masculine	–0.008	–0.009	–0.006
	(0.013)	(0.014)	(0.028)
Constant	2.188***	2.191***	2.196***
	(0.018)	(0.015)	(0.027)
Observations	20009	15239	4770
Mean Y	2.148	2.170	2.077
Controls			
Caste FE		✓	✓
City × Caste FE	✓		
Education FE	✓	✓	✓
Male profile controls	✓	✓	✓

Notes: In panel A, the dependent variable is the log of male suitor's income (mid point of the stated income interval) and in panel B, it is highest level of education of the suitor (1 - High school/Diploma ; 2 - Bachelors, 3 - Masters). The main explanatory variable, 'Not working' takes a value of one for a fictitious female profile who is currently not employed and zero otherwise; 'Masculine' takes a value of one if a fictitious female profile is engaged in a masculine occupation and zero otherwise; 'Neutral' takes a value of one if a fictitious female profile is engaged in a gender neutral occupation and zero otherwise. The reference group for occupation type is females profiles engaged in feminine occupations. Details on occupational classification based on gender distribution are discussed in section 3. Controls include female profiles' education, caste category and city of residence; interacting male profile's highest level of education (not in panel B), age, height, caste category, profile manager (self/parent/managed by others), income (not in panel A) and whether income is less than that of the corresponding fictitious female profile. Standard errors clustered at the level of the interacting male's (suitor) profile in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A.12: Effect of Female Work Status on Male Interest (by Manager of the Interacting Male Profile)

	(1)	(2)	(3)	(4)	(5)	(6)
	Managed by Parents/Relatives			Managed by Self		
	Overall	Delhi	Bangalore	Overall	Delhi	Bangalore
Working	–0.004*	–0.007**	0.012*	–0.010***	–0.012***	–0.005
	(0.003)	(0.003)	(0.006)	(0.002)	(0.002)	(0.004)
Constant	0.111**	0.063	0.125	0.030	–0.001	0.097
	(0.049)	(0.044)	(0.177)	(0.042)	(0.041)	(0.111)
Observations	94437	81018	13419	232407	182448	49959
Mean Y	0.058	0.056	0.071	0.064	0.060	0.079
Controls						
Caste FE		✓	✓		✓	✓
City × Caste FE	✓			✓		
Education FE	✓	✓	✓	✓	✓	✓
Male profile controls	✓	✓	✓	✓	✓	✓

Notes: The dependent variable is an indicator variable that takes a value of one if a fictitious female profile received an interest from a male profile and zero otherwise. The main explanatory variable, 'Working' is an indicator variable that takes a value of one for a fictitious female profile who is currently employed and zero otherwise. Controls include female profiles' education, caste category and city of residence; interacting male profile's highest level of education, age, height, caste category, profile manager (self/parent/managed by others), income and whether income is less than that of the corresponding fictitious female profile. Standard errors clustered at the level of the interacting male's (suitor) profile in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.13: Effect of Female Work Status on Male Interests (by Female Education)

	(1)	(2)	(3)	(4)
	Overall	Diploma	BA	MA
Panel A : Overall				
Working	–0.009***	–0.011***	–0.007***	–0.008***
	(0.001)	(0.002)	(0.002)	(0.002)
Observations	329427	109809	109809	109809
Mean Y	0.0623	0.0584	0.0632	0.0653
City × Caste FE	✓	✓	✓	✓
Education FE	✓			
Male profile controls	✓	✓	✓	✓
Panel B : Delhi				
Working	–0.010***	–0.013***	–0.008***	–0.010***
	(0.002)	(0.002)	(0.002)	(0.002)
Observations	265545	88515	88515	88515
Mean Y	0.0586	0.0550	0.0589	0.0619
Panel C : Bangalore				
Working	–0.002	–0.004	–0.002	0.001
	(0.004)	(0.005)	(0.005)	(0.005)
Observations	63882	21294	21294	21294
Mean Y	0.0776	0.0725	0.0811	0.0792
Caste FE	✓	✓	✓	✓
Education FE	✓			
Male profile controls	✓	✓	✓	✓

Notes: The dependent variable is an indicator variable that takes a value of one if a fictitious female profile received an interest from a male profile and zero otherwise. The main explanatory variable, 'Working' is an indicator variable that takes a value of one for a fictitious female profile who is not currently employed and zero otherwise. Column (1) shows the overall effect while columns (2)-(4) show the effect by the highest education level of the female profile. Controls include female profiles' caste category and city of residence; interacting male profile's highest level of education, age, height, caste category, profile manager (self/parent/managed by others), income and whether income is less than that of the corresponding fictitious female profile. Standard errors clustered at the level of the interacting male's (suitor) profile in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A.14: Effect of Female Work Status on Male Interest (by Education of the Interacting Male)

	(1)	(2)	(3)	(4)
	Overall	Diploma	Bachelors	Masters
Panel A : Overall				
Working	–0.009***	–0.031***	–0.006***	0.001
	(0.001)	(0.005)	(0.002)	(0.003)
Observations	329427	49014	172179	86247
Mean Y	0.0623	0.0667	0.0592	0.0679
City × Caste FE	✓	✓	✓	✓
Education FE	✓	✓	✓	✓
Male profile controls	✓	✓	✓	✓
Panel B : Delhi				
Working	–0.010***	–0.037***	–0.007***	–0.002
	(0.002)	(0.005)	(0.002)	(0.003)
Observations	265545	38052	140742	69993
Mean Y	0.0586	0.0577	0.0566	0.0643
Panel C : Bangalore				
Working	–0.002	–0.010	–0.001	0.014*
	(0.004)	(0.011)	(0.005)	(0.007)
Observations	63882	10962	31437	16254
Mean Y	0.0776	0.0979	0.0706	0.0836
Caste FE	✓	✓	✓	✓
Education FE	✓	✓	✓	✓
Male profile controls	✓	✓	✓	✓

Notes: The dependent variable is an indicator variable that takes a value of one if a female profile received an interest from a male profile and zero otherwise. The main explanatory variable, 'Working' is an indicator variable that takes a value of one for a fictitious female profile who is not currently employed and zero otherwise. Column (1) shows the overall effect while columns (2)-(4) show the effect by the education of the interacting male profile. Controls include female profiles' education, caste category and city of residence; interacting male profile's highest level of education, age, height, caste category, profile manager (self/parent/managed by others), income and whether income is less than that of the corresponding fictitious female profile. Standard errors clustered at the level of the interacting male's (suitor) profile in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

B Data Appendix

We first describe the secondary datasets used in this study in Section B.1 and Section B.2. We then explain in detail the construction of the female profiles on the marriage market platform in Section B.3.

B.1 Time Use Survey (TUS)

Time Use Survey data are from 138,799 households across all states of India conducted in 2018-19. The TUS adopted the interview method method for collection of data since not all respondents are literate enough to maintain time diaries. A reference period of one week was used for collecting the data. To capture the variation in the activity pattern, data were collected for two types of days - normal and others - with a recall lapse of one day, i.e., a 24 hour recall with actual time spent in minutes recorded for each activity.

Classification of activities: We followed standard classification of time use activities for total market work (labor) and total non-market work (domestic work) as in Aguiar & Hurst (2007).

(a) Time spent in labor market: farming, animal husbandry, fishing, food processing, collection of fruits/vegetables/fodder/forest produce, mining, construction, manufacturing, trade, business, services, travel to work and in search of job (paid and self employed labor which includes both formal and informal type of work).

(b) Time spent on domestic work: Fetching water (for drinking at home), collecting fuelwood (for cooking at home), household maintenance activities like cooking, cleaning, shopping for household supplies, supervising household work, repair of household goods, pet care, travel related to household maintenance, care for - children, the sick, the elderly and the disabled, non-formal education of children.

B.2 Consumer Pyramids Household Survey (CPHS)

Consumer Pyramids Household Survey is a panel data collected every quarter by the CMIE. We use CPHS from two quarters - September - December 2021 and January - April 2022 where 134,436 and 133,671 households were surveyed, respectively. We keep only urban married women aged 20-45 for the analyses. Over these quarters 68,861 and 68,374 women were sampled in this demographic category, in September - December 2021 and January - April 2022 quarters, respectively.

The CPHS data provide time use across 11 categories - time spent for employer, on household work, as unpaid trainee, voluntary work, unpaid trainee, travel, learning, religious work, sports, indoor entertainment and other leisure activities. The respondents are asked the hours spent in each of the 11 aggregate categories on the previous day. This is unlike the TUS data which uses detailed activity classification (International Classification of Activities for Time Use Statistics 2016 (3-digit codes)) with the diary method of recording data on an hourly basis in the previous 24 hours.

The CPHS captures the employment status as of the date of the survey. If an individual is engaged in any economic activity either on the day of the survey or on the day preceding the survey or generally regularly engaged in an economic activity she/he is considered employed (even if unable to work in the past few days due to illness or other contingencies). Among the individuals who report themselves to be not employed, the survey further records their alternative status - unemployed, willing and looking for a job; unemployed, willing but not looking for a job; and unemployed, not willing to work and not looking for a job. The CPHS also records the details of employment, including the nature of occupation (19 categories), the industry of occupation (38 categories), type of employment (full time/part-time) and employment arrangement (casual labor, salaried (permanent/temporary), self-employed).

Afridi *et al.* (2022a) provide a detailed comparison of the CPHS data with the PLFS data. Broadly, they show that employment rates for men are mostly comparable while those for women are almost half for women in the CPHS using usual or weekly status but three-fourths using the daily status definition in PLFS. The differences are starker for urban women (13.7% in the PLFS using daily status vs 9% in the CPHS). One reason for the difference in women's employment rates could be the framing of the questions across the two surveys. They find, however, that the broad patterns across regions and demographic groups for women are similar across the two data sources. Therefore, using the CPHS for relative comparisons across groups, despite low average levels, should not be problematic.

B.3 Female Profile Creation on the Matrimonial Platform

As described in Section 3, we chose to vary only a select number of characteristics of each of our fictitious female profiles for each city - employment status, occupation of those employed, preference to work post marriage, education and caste. The combination of these characteristics are as shown in Figure 2 for the fictitious female profiles for ease of representation. While the platform pre-specified the fields for providing information on employment, occupation, caste and education, the profile's preference to work was mentioned in the field called *Describe yourself briefly.*

Apart from the above fields, we scraped data from the platform to arrive at the *average* profile on the platform for some of the optional fields. Although these fields were optional, most profiles on the platform provided information on these characteristics and hence to avoid any suspicion from potential suitors we assigned average values to them. All other fields on the profile page were either assigned the same values/information (depending upon the city of experiment) or left blank. We provided additional information for the following characteristics:

- **Full Name**: The full name of the user. It is not visible to interacting men, but we assigned one anyway from a list of common names and last names (as per assigned caste of the fictitious profile).
- **City**: The city of the user. Half the profiles were assigned to Delhi and the other half to Bangalore.
- **Caste**: The caste of the user. The platform provides a list of castes from a drop-down menu. For each city, we assigned either *Brahmin*, *Scheduled Caste*, or Other high castes (Vokkaligga (Bangalore)/ Bania (Delhi)) to the profiles.
- **Occupation**: The occupation of the user. The platform provides a drop-down menu containing a list of occupations ("Not Working" is one of the categories). We assigned one of our chosen occupations (Or "Not Working") to each profile.

- **Highest Education Level** : The highest education level attained by the user. The platform provides a drop-down menu containing a list of degrees (or High School / Diploma). We assigned each user either “Diploma", “BA", or “MA".

- **About You**: A long-form description of the user. We generated a description that included personal qualities, hobbies, and education. Hobbies and personal descriptions were kept constant across profiles although the sentence structure was reorganized for each profile. For employed profiles, the generated paragraph also contained a sentence to express work preference after marriage.

- **Family Description** : A long-form description of the user's family. We generated a generic set of lines containing information about siblings and family values. The sentence structure was changed and the sentence order was randomized across profiles, keeping the same content, e.g. "We want a compatible and very well-settled family for the match. I have a brother. We have a very strong focus on values and spend a lot of time together. We are good-natured and thoughtful. We are all very supportive as a family." vs "We are all good-natured and understanding. We like spending time together and have very strong values. We are looking for a very well-settled and similar-minded family. I have one brother."

- **Sector of Employment**: For an employed profile this field shows the sector of employment based on choices provided in a drop-down menu. We assigned ‘Private’ for all employed female profiles and kept it blank for all ’not working’ female profiles.

- **Family Type**: This describes the family type of the user based on choices provided in a drop-down menu. All profiles were assigned ‘Nuclear’ family.

- **Family Based**: The field reports the city where the user's family is based. We assigned either Delhi or Bangalore (the same as the city assigned to the profile) for this field.

- **Smoking**: A 'yes/no' drop-down for whether the user smokes. We assigned 'No' to each profile.

- **Drinking**: A 'yes/no' drop-down for whether the user drinks. We assigned 'No' to each profile.

- **Languages Spoken** : The languages spoken by the the user. We assigned English and Hindi to profiles that were assigned Delhi and; English, Hindi, and Kannada to profiles that were assigned Bangalore.

- **Marital Status**: The marital status of the user based on choices provided in a drop-down menu. We assigned all profiles 'Never Married'.

- **Annual Income**: The annual income of the user when employed. The platform provides a drop-down menu containing income brackets. We assigned INR 0.3-0.4 million for each employed profile.

- **Family Income**: The annual household income of the user. The platform provides a drop-down menu containing income brackets. We assigned INR 0.55-0.75 million for each employed profile.

- **Age** : This field states the age of the user. We assigned the age of 25 years to each female profile.

- **Height** : This field states the height of the user. We assigned '5 feet 3 inches' to each female profile.

- **Number of Brothers** : This field states the number of brothers of the user. We assigned each profile 1 in this field.

- **Number of Sisters** : This field states the number of sisters of the user. We assigned each profile 0 in this field.

- **Family Status**: The economic status of the user's family based on drop-down menu. We assigned each profile the status of "Middle-clas".

- **Family values**: The value system of the the user's family based on choices provided in a drop-down menu. Each profile was assigned "Moderat".

- **Mother's occupation**: The occupation of the user's mother, assigned from a drop-down list. We assigned "Housewife" to each female profile.

- **Father's occupation**: The occupation of the user's father, assigned from a drop-down list. We assigned "Service - Private" to each female profile.

- **Profile Manager**: The person managing the user's profile based on a drop-down menu. We assigned "Self" for each female profile.