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

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Abstract

We conduct an experiment to elicit preferences for partners on an online marriage market platform in India. We find that working women are 12.8% less likely to receive interest from male suitors. Additionally, women employed in 'masculine' occupations are 3.3% less likely to elicit interest from suitors relative to those in 'feminine' occupations. Men hailing from higher castes and northern India, where communities have more conservative gender related preferences, are less likely to show interest in working women. Our results highlight the role of patriarchal gender attitudes in marital preferences and suggest that expectations regarding returns in the marriage-market may influence women's labor market choices.

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1 Introduction

A nascent literature in economics has analysed factors which influence partner matching (in dating and marriage markets), including 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.

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 platform. Unlike newspaper adverts 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, 2023). 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 fictitious 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 in nationally representative surveys. The occupational gender stereotypes represent the extent of social acceptance of women's work choices based on extant gender roles, such as those which 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).

We tailor the full set of profiles to two cities - Delhi (North India) and Bangalore (South India). This allows us to assess any effects of spatial heterogeneity on gender related preferences and practices, which have been extensively documented to be more gender unequal in the north relative to the south of the country due to historical cultural differences (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 range (if applicable) are held constant across profiles.

Our results highlight the role of patriarchal gender attitudes in shaping marital preferences. On average, employed women are 12.8% less likely to receive interest from male suitors relative to women who are not working. The greater preference for female partners who are not working, holds across all education groups. Moreover, women employed in 'masculine' occupations are 3.3% less likely to receive interest 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.

These results are driven by responses from higher caste men in north India (Delhi), where patriarchal gender preferences - lower value attached to working women and a disproportionate burden of household work on women - are more salient. We also verify that male suitors

residing in states having more patriarchal attitudes and where women spend a greater share of time in domestic work are less likely to express marital interest in working women and those working in male-dominated occupations. We discuss and rule out alternative explanations for our findings, such as search costs, perceived risk of sexual harassment and social status associated with certain occupations.

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 bases their interest on job status or job prestige on Tinder but men initiate a conversation less frequently with women who are unemployed. On the other hand, we show that existing patriarchal and regressive gender preferences can be a strong determinant of partner choices in developing country contexts. Our results extend Dhar (2023), whose pilot study on a separate matrimonial platform 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. In this vein, we contribute to a broader literature which shows how women and families make choices related to work and education, including foregoing important benefits, in order to improve their outcomes on the marriage market (Bursztyn *et al.*, 2017; Andrew & Adams, 2022; Maertens, 2013; Buchmann *et al.*, 2023; Beauchamp *et al.*, 2022). Our findings resonate especially with Bursztyn *et al.* (2017) who find that women project themselves to be less ambitious in the presence of their male peers.

We also contribute to the literature on marriage market gaps across skilled and educated women. Hwang (2016) and Bertrand *et al.* (2020) 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.* (2020) 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 gender attitudes and biases 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.

Finally, 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 existence of gender-job associations in a society can lead men and women to take on gender typical roles at work (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 discuss potential mechanisms that explain our findings and conclude in Sections 6 and 7, respectively.

2 Background and context

In this section, we provide the context for our study based in urban India, and the relevant cultural norms and gender attitudes.[4] 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 between genders narrowing over time. We highlight some indicators of patriarchal gender preferences, such as the gender-based division of labor where women bear a disproportionate burden of home production. The gendered division of labor is also likely to be correlated with other social attitudes which restrict women's physical mobility and social interactions, such as sexual purity (Agte & Bernhardt, 2023; Chakraborty et al., 2018), for which data are either absent or less reliable. We, therefore, first discuss the overall gender gap in time use and thereafter

the spatial and socio-economic (caste) variation in gender gaps in India.

2.1   Gender gap in intra-household time allocation

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), indicating the prevailing preferences related to the time allocation of women after marriage. This is held up by both the nationally representative Time Use Survey (TUS, January-December 2019) and the Consumer Pyramids Household Survey (CPHS, September 2021-April 2022), which also provides information on occupation unlike the TUS (Appendix Figure A.1). For instance, married men (irrespective of education) spend only one hour per day undertaking household work, whereas married women spend nearly 8-9 hours per day (see Appendix Figure A.1 (b)). Interestingly, the U-shape of women's time spent in the labor market with education cannot be explained by returns to education (Afridi *et al.*, 2022b) which increase monotonically (Appendix Figure A.2).

Notably, married women who are employed spend 60-70% less time on domestic work, relative to married women who are not in the work force (Appendix Table A.1). Next, we classify each occupation in the CPHS into 3 types – male dominated, gender neutral and female dominated.[5] 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 gender neutral occupations spend 50% – 60% and 10% – 18% less time on domestic work, 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 demanding or inflexible working schedules (Goldin, 2014; Chaturvedi *et al.*, 2022). Moreover, the daily wage rate decreases as the proportion of women workers increase in an occupation (Appendix Figure A.3).[6]

2.2 Heterogeneity in gender gaps

Dyson & Moore (1983) contrast states in the north of India with the southern states on patriarchal attitudes and related gender outcomes. They note that the south is not only characterized by higher female labor market participation, but also later age at marriage, lower marital fertility and, in general, a higher status of women.[7] Studies point to different explanations for these regional differences ranging from kinship structures to historical cropping patterns.[8] These regional differences are also confirmed by the more recent Index of Patriarchy for Indian states by Singh *et al.* (2022), constructed using the National Family Health Survey (NFHS-4, 2015-16).[9]

The spatial heterogeneity in labor force participation of married women is also reflected in the gender gaps in time allocation across the north and the south of India. (Boserup, 1970; Dyson & Moore, 1983; Chen, 1995; Das, 2006; Mahajan & Ramaswami, 2017).[10] Married women in the north spend relatively less time than married men in the labor market (Appendix Table A.3, Panel A, columns 2 and 4) in comparison with their southern peers. On the other hand, married women in the north spend more time than their male counterparts on domestic work, in comparison with the south (columns 1 and 3).[11] Moreover, we find a strong, positive correlation ($p=0.006$) between the state level Patriarchy Index (Singh *et al.*, 2022), with the proportion of time spent by (married) women in domestic work from the Time Use Survey (Appendix Figure A.4).

Additionally, married women belonging to higher castes spend less time in the labor market and more time undertaking domestic work (Appendix Table A.3, Panel B), in line with the literature on restrictive gender norms on female purity and male breadwinner status being more stringent for upper caste households (Eswaran *et al.*, 2013; Agte & Bernhardt, 2023). These findings underscore the salience of spatial and caste based differences in gender roles 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). Further, using data on married couples in the National Sample Surveys, Afridi *et al.* (2022b) find that women are more likely to marry men who have an education either equal or exceeding their own education. For instance, 57% women who have completed school (but not college) marry men having school education and 30% marry men who are at least college educated. However, 86% women who are college educated marry men who have also completed college. Thus, positive assortative matching on education, coupled with increasing market returns (i.e., wages) to higher levels of education (Appendix Figure A.2), suggest that more educated women may have higher returns in the marriage market in India.

The importance of matchmaking by families in India, also known as "arranged" marriage, is well recognized. Indian Human Development Survey (2011-12) shows that 95% marriages in urban India are arranged (Kaur & Palriwala, 2014), with only a marginal decline over the last decade (Allendorf & Pandian, 2016). A recent Lok Foundation-Oxford University survey in 2018 among 20-30 years old married youth also shows that 90% married through the custom of arranged marriage. This prevalence was larger in the northern states compared to the southern states. Notably, marriages typically happen within the same caste in India. Around 94% of all marriages were intra-caste in 2011 (Ray *et al.*, 2020).

Historically, parental preferences have played a major role in partner selection in "arranged" marriages in India, reinforcing social stereotypes and cultural norms (see Anukriti & Dasgupta (2017) for a review). For instance, 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 preferences play out in the marriage market and whether they perpetuate when new matching technology allows younger generations to be more active participants in decisions

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related to partner selection. Increased adoption of digital platforms for dating and marriage provides an opportunity to analyse individuals' partner preferences.

Over time, matchmaking has evolved 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 report 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, such as 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).

3 Experiment design

We conducted an experiment to understand marital preferences on a leading online match-making platform in India, with over 0.4 million active users in a given month. User profiles on the platform are of individuals on the marriage market who are looking for a match. A comparative analysis of users on the platform with the never married population in India, using the PLFS (2018) data, shows that male and female users are likely to be older, more educated, more likely to be employed or earn a higher income when employed, and less likely to hail from a Scheduled Caste (SC) background, compared to the average population of never married adults in India.[12] This matrimonial platform, therefore, largely caters to relatively more educated and middle to upper-middle class families. In this regard, we discuss the external validity of our findings later.

In our experiment, we uploaded fictitious female and male profiles on the platform and studied the interests received by these profiles over a period of a month after being created. Our experiment is based on the premise that an expression of interest by a user to connect on the platform indicates a preference for a potential match with that profile. We assume that expressions of interest reflect the marital preferences of the user, in that the net benefit of expressing an interest is positive. To elaborate, a (male) profile incurs costs (e.g. time spent) in searching, scanning and sending interests to (female) profiles, while the benefit of the search and sending interests is the expected probability of receiving a response and eventually a match. A (male) profile is likely to send an interest to a (female) profile only if the net expected benefit is positive. Hence an expression of interest should be aligned with marital preferences.[13]

We uploaded the 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). In addition, we varied the stated occupations, based on gender stereotypes, among the employed female profiles. 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 in the text description, which was included in the profile. Thus, in total one unemployed female profile and six employed female 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 (BA) and Master of Arts (MA). This led to a total of *21* female profiles. All the fabricated profiles belonged to Hindu religion since this is the predominant religion (80% of the population) in India and almost 98% of marriages for women between the ages of 15-49 are within the same religion (India Human Development Survey 2004-5). Figure 1 depicts the design of the fictitious 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 PLFS (2018-19) of India. We estimated the share of women employed across occupation categories by education (Appendix Figure A.5), keeping 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. 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 India. Based on the above criteria, we shortlisted occupations where women constituted more than 50% of employees, based on the PLFS 2018-19, into the 'Feminine' category. We classified occupations where they constituted between 15-35% of the workforce into the 'Neutral' category. Finally, the occupations where women made up less than 10% of the

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workforce were classified as 'Masculine' occupations.[14]

Finally, we chose nine occupations from this set, across the three education categories, to reflect each occupation type within each education category.[15] These were selected on the basis of being distinct in terms of female presence, with gradations along the education spectrum and being available to students graduating in an Arts degree so that gender differences across STEM and non-STEM major choices would 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. In 2011, 5.82% of all marriages were inter-caste (Ray *et al.*, 2020). We, thus, classified the profiles into the following three caste categories - Brahmins (Upper Castes), Other High Castes (OHC), Scheduled Castes (SC).[16] Thus, in total we created $21 \times 3 = 63$ female profiles and uploaded them on the matchmaking platform.[17]

None of the fictitious profiles carried a photograph. Including photographs would have an additional risk of perceived beauty becoming a confounding factor. Also, the platform allows profile creators to hide photos for digital privacy and only reveal them to profiles of the opposite sex whom they would like to interact with. Thus, at the time of sending an interest, it is not possible for a male suitor to know whether a female profile has a hidden photo or no photo. The other characteristics of the profiles, e.g. age, height, manager of the profile, number of siblings and composition, household income range and own income range and nature of job as public or private (for those employed) were held constant. Public (government) jobs are accorded a higher status in the Indian marriage market than private

jobs. All working profiles were indicated as being employed in the private sector – thus holding constant this major factor affecting job status. Further details on profile creation and the values assigned to characteristics 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.[18] 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). We also tailored the 'Other High Caste' category to the city of the profile since the sub-categories within this caste are region specific in India. 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. This is because we largely expect men from similar region to interact with our female profiles since inter-state migration rates are low in India (Munshi & Rosenzweig, 2009). In fact, the share of inter-state migration is less than 10% for Indian women (Census 2011).

We followed the same process for creation of the fictitious male profiles - except that there was no stated preference for work after marriage in these profiles. Given the above design, there were overall 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 from 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.

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).[19]

If a male user on the platform sent an expression of interest to any fictitious female profile we consider that user to be 'interested' in that female profile. Of all the interests received from male profiles on the platform, 50% were singleton (Appendix Figure A.6), suggesting that there may be some search costs that are incurred in sending interests. On average, four interests were sent by each male suitor across our fictitious female profiles. 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.[20] 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.[21] On average, a fictitious female profile received expressions of interest from 6.2% males.

Next, we examine the proportion of male suitors that demonstrated interest based on the employment status and occupation type of the female profiles we created. On average, female profiles that stated 'not-working' as the employment status received the most attention with expressions of interest from 7% of male profiles, while female profiles working in 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. We acknowledge the possibility of sample selection due to the platform's algorithm that can influence male profiles' exposure to our fictitious female profiles and thereby confound our 'interest' outcome. Hence, we interpret our results accounting for selection and also discuss this issue later.

We also check whether male interests vary based on search costs driven by the expected probability of the female profile reciprocating. Appendix Table A.8 shows the average characteristics of men who expressed interest by the working status of the fictitious female profile - male suitors who sent interests to 'Not Working' profiles only (column 1), 'Working' profiles only (column 2) and both types of female profiles (column 3).[22] The differences in mean characteristics between pairs of these exclusive categories of male suitors are shown in columns (4) - (6). We find that those who expressed interest in only working female profiles are younger, less likely to be employed, earning a higher income, more like to belong to SC/ST caste category and more educated. Search costs (in terms of opportunity cost of time) are likely to be higher for employed, higher income and more educated male suitors. On the other hand, they may have a higher expected probability of obtaining a response from a working female profile since the existing literature shows that women value income earning potential in men (Fisman *et al.*, 2006; Hitsch *et al.*, 2010). Greater interests towards working women by higher income and more educated male suitors conform to a higher probability of reciprocation. However, greater interests towards working women by lower caste men do not, and likely reflect the preference channel instead. This suggests that expressions of interest (and search behavior), between working and non-working female profiles, do not

vary systematically by male suitor characteristics that may proxy for a higher probability of reciprocation from working women.

4   Estimation strategy

As discussed earlier, 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. This strategy is similar to some of the existing papers in the context of marriage market preferences (Dugar *et al.*, 2012) as well as other studies on job preferences where the observed characteristics of applied jobs are used to infer the potential choice set of a job seeker (Le Barbanchon *et al.*, 2021). In this case, we use the characteristic of sending an interest to a profile in a particular city to construct the choice set of a male suitor. We later refine these on basis of other characteristics such as caste. We then estimate whether fictitious female profiles who were working received any differential display of interest from potential male suitors on the platform using the below specification:

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

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

interests received across the female profiles we created. Additionally, we control for a host of characteristics of the (non-fictitious) male profiles (X_j) in our preferred specification. 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. We add these controls to allay any concerns that there was a non-random element in uploading the female profiles such that the working status of the fictitious female profiles differed by search spells of suitors who either had differential preference for working women or search costs. If the female profiles were randomly uploaded on the platform then male suitor characteristics should not affect our results. Indeed, as we discuss later, our results are insensitive to controlling for male suitor characteristics.

The coefficient β_1 is the main parameter of interest. Notably, given the construction of the sample, where we only keep male suitors who have shown an interest in at least one of the created female profiles, the interpretation of the parameter cannot be undertaken in percentage points. This is because we do not have the entire universe of suitors who could have potentially interacted with our female profiles. However, what we can accurately estimate is the percentage difference in interests towards working vs. non-working female profiles. This can be done by dividing the parameter by the average of the dependent variable for the base group of non-working female profiles. Mathematically, this is given by $(\beta_1/\bar{Y}_{NW})$ where $\bar{Y}_{NW}$ is the average probability of receiving an interest for not working female profiles. 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 relative 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 (Fisman *et al.*, 2006).

In the next specification, we examine whether expressions of interest by male profiles

differ across occupational categories of the fictitious female profiles:

$$Y_{icsj} = \beta_0 + \delta_1 Masculine_i + \delta_2 Neutral_i + \delta_3 Not\ working_i +$$

$$\beta_2 Education_i + \gamma_{cs} + X_j + \epsilon_{icsj} \quad (2)$$

where $Masculine$ is an indicator variable that equals one if the female profile is indicated as working in a 'masculine' occupation and zero otherwise; $Neutral$ equals one if the female profile is shown to be working in a gender-neutral occupation and zero otherwise; $Not\ working$ equals one if the female profile is described as not employed/working in the labor market. Here, $\delta_1/\bar{Y}_F$, where $\bar{Y}_F$ is the average probability of receiving interests by female profiles employed in feminine occupations, shows the percentage difference in the probability of receiving an expression of interest by women employed in masculine occupations vs. women employed in feminine occupations. Similarly, $\delta_2/\bar{Y}_F$ and $\delta_3/\bar{Y}_F$ show the percentage difference in the probability of receiving an interest by women employed in gender-neutral occupations and by women who are not working in comparison to women employed in feminine occupations, respectively.

5 Results

5.1 Main results

Table 2 shows the estimates from Equation 1 for both cities in column (1) and disaggregated for Delhi and Bangalore in columns (2) and (3), respectively. Panel (A) shows the results without controlling for suitor characteristics and panel (B) shows the results after controlling for these.[23] We find similar results across both panels. On average, a not working female profile receives expressions of interest from 7 percent male suitors on the platform. However, working or employed female profiles receive 12.8% (=0.009/0.07) lower interests from male suitors (Panel B, column 1). 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 15% less likely to receive a response relative to their peers who are not working. 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. Notably, the largest proportion of interests (92%) received by Delhi based fictitious female profiles are from male suitors residing in the north while 67% interests received by Bangalore based female profiles are from male suitors residing in 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 by estimating Equation 2. Table 3, Panel (A) shows the results without controlling for suitor characteristics while Panel (B) shows the results after controlling for these. Again, we find similar results across both the panels and discuss the one from our preferred specification in Panel B. Column (1) shows that female profiles employed in 'masculine' occupations are 3.3% (= 0.002/0.061) less likely to receive an expression of interest compared to those employed in 'feminine' occupations. There is no 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 13% (= 0.008/0.061) 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 working receive 5.2% lower and 15.5% greater interest, respectively, as compared to women employed in 'feminine' occupations. To benchmark the magnitude of these effects, we compare them to other studies in the literature. For instance, Fisman et al. (2006) find that men are 16% less likely to contact women who they rate as being more ambitious than them on an online dating platform in the United States. This

comes close to the overall penalty faced by working women in our experiment of 12.8%.

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. On the other hand, 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 male suitors based on their caste category, age, height, profile manager, income, education, 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 results. We continue to find a 11.6% decrease in probability of receiving an expression of interest for a working female profile relative to non-working female profiles. This result, as before, is driven by the profiles in Delhi where an employed female profile is 15% 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 3.3%

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.[24]

5.2 Heterogeneity

In this section we examine the heterogeneity in our findings by caste and education.

Caste: Recall the variation in gender attitudes across castes discussed in Section 2.2. 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) show the estimates for Brahmin, Other High Castes and SC female profiles, respectively. Panel A shows that the 12.8% lower probability of receiving an interest seen for employed female profiles is a high caste phenomenon. It is driven largely by the lower interest in working profiles that are Brahmin (13% lower) and Other High Castes (18% lower). On the other hand, the working SC 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 19.7% and 20.2% 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; Agte & Bernhardt, 2023).

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% interests by Other High Caste men are towards same caste or Brahmin females and 71% interests 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 also examine the heterogeneity in our results by caste of the 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. Working Brahmin female profiles receive 12.3% 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 14.7% 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 working status of the female profiles across castes in the south.[26]

In the appendix, we show 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.10. 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 (column (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 in Appendix Table A.11. 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. The results by caste of male suitors towards Delhi based profiles lend support for the hypothesis that higher caste men show less inclination for women in 'masculine' occupations in the north. These results for caste groups continue to hold even after controlling for the income of the male suitor (Appendix Tables A.12 and A.13).[27]

Education: Can higher female education weaken regressive gender attitudes 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.[28] Appendix Table A.14 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.[29]

Next, we examine heterogeneity in our results by the education level of male suitors. Higher education for men can possibly increase exposure and erode regressive gender attitudes. 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.15, 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 and Masters education levels,

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respectively. The overall results in Panel A show that working female profiles have a lower probability of receiving interest from male suitors with a Diploma and Bachelors education but male suitors with a Masters education do not penalize working women. The degree of penalty for working women is also lower from male suitors having Bachelors (9.2%) vs Diploma (33%) 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.

5.3   Caveats

There are a few limitations and caveats to our findings above. 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 have conducted an extensive list of heterogeneity analyses by education, caste, and location to address external validity issues. These results indicate that less educated women are more likely to receive a penalty and that less educated men are more likely to place the penalty on working women. Thus the marriage market penalty on working women may be higher in the population (in India) than on the platform itself.

Another potential limitation of this study is that of algorithmic exposure, inherent in many commercial online sites and services, which push content at users. We have addressed this concern, however, by interpreting our coefficients appropriately throughout in terms of the percentage lower interests received by working female profiles (calculating this over the average probability of receiving interest by non-working female profiles). While potential differential exposure of certain types of female profiles to male suitors was not in the control of this research study, the actual viewing of our fictitious female profiles, conditional on algorithmic exposure, may itself indicate the preferences of male suitors on the matchmaking platform. For instance, a male suitor on the platform can indicate that they prefer not-

working, own caste or declare minimum education criteria for women they seek. The platform algorithm would then highlight female profiles who match these criteria to them. In this case, not expressing an interest in a working female profile that we create (because it was not viewed) allows one to capture such algorithmic behaviour.[30] Lastly, while our analysis does not allow us to completely disentangle taste-based versus statistical discrimination (arising from search costs) as the drivers of our findings, our results highlight the salience of patriarchal attitudes that manifest in lower interest received by employed women from male suitors on the match-making platform. We discuss this issue in detail in the next section.

6   Mechanisms

Our findings indicate that men are more likely to express interest in potential partners who do not work, or alternatively, if they do work, are engaged in occupations that are 'feminine' i.e., with a greater proportion of female workers (associated with more flexible and limited work hours and also safer for women). Higher castes and north Indian men are more likely to exhibit such behavior. In this section we discuss plausible mechanisms that can explain our findings.

6.1   Gender attitudes

We attribute the observed behavior of male suitors on the platform to male preferences that stem from regressive or traditional gender attitudes regarding women's role in society, and provide more evidence in support of this mechanism below.

Using the state level India Patriarchy Index (Singh *et al.*, 2022), discussed earlier in Section 2.2, we examine the heterogeneity in men's marriage market preferences for working women by gender attitudes prevailing in the state of residence of the male suitor. We standardize the state level index for ease of interpretation and report the heterogeneous results in Appendix Table A.19 based on the patriarchy index of the state in which the

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male suitor resides. Column (1) shows that a one standard deviation increase in the index, indicating a higher level of patriarchal gender attitudes, lowers the probability of receiving an expression of interest by a working female profile by 11.3%. This further confirms that working women are more likely to be penalized by male suitors from states having higher prevalence of patriarchal gender attitudes. Column (2) shows that this penalty is driven by male suitors residing in the most conservative states i.e., those having index values in the top-most quartile.

In columns (3)-(4), we estimate the heterogeneity in interests received by working female profiles based on the proportion of time spent on domestic work by women in the state of the male suitor's residence. For each state, we calculate the share of time women spend on domestic work out of the total time spent by both women and men on domestic work (*DW Share*) and standardize the share across states. The result in column (3) shows that male suitors residing in states where women undertake a higher proportion of domestic work are less likely to send interests to working women, driven by the top quartile of states (column 4). In fact, suitors from states where women's share of domestic work lies in the top quartile penalize working women by almost 1.6 times more than suitors in the other states.

Further, Appendix Table A.20 shows results by occupation type. Once again, we find that male suitors in more conservative states, with higher patriarchy index values, are more likely to express an interest in female profiles that are not working. In fact, the penalty on women employed in masculine and neutral jobs are driven by male suitors in the most conservative states, belonging to the top quartile of the patriarchy index (column 2). The results using *DW Share* show a similar pattern - men are more interested in non-working women and those in feminine occupations in states where women share a higher burden of domestic work.

6.2 Alternative explanations

We examine and rule out alternative channels that could entirely explain our findings, to provide further evidence in support of gender attitudes as the main driving mechanism.

Search costs: Search costs may vary due to the opportunity cost of time and expected reciprocity. To elaborate on the latter, men may express lower interest in working women if they expect these women to be more discerning about potential partners and hence, more likely to reject their interest. Hence men may perceive the net expected benefit of expressing interest in a working woman to be lower. The lower preference for working women due to higher search costs is akin to statistical discrimination. However, we conduct a battery of tests and find that our results cannot be explained by differential search costs between working and non-working female profiles.

First, recall our discussion in Section 3.1 showing that there is no systematic variation in the characteristics of male suitors who express interest in working female profiles versus those who send interests to non-working female profiles. Since male characteristics are a reasonable proxy for the probability of reciprocation from a female profile (e.g. employed or highly educated men are more likely to elicit a positive response), this suggests that there is little variation in search costs by expected reciprocation on the platform. Second, since a working woman may be more likely to decline interests from less educated men or those with lower income than hers, we analyze the data for males who have at least as high education or at least as high income as the fictitious female profile (Appendix Table A.21, Panels A and B). Our results continue to hold for these subsets of men as well. In fact, we find that even men with a graduate degree display lower interest in working women (Appendix Table A.15). Thus, even educated men who have higher chance of reciprocation from women impose a substantial penalty on working women. Third, past rejection faced by men from a working female profile may dissuade them from future expressions of interest towards such profiles on the platform. Younger male profiles, however, are less likely to have learnt about preferences of working women due to shorter experience on the marriage market. Search costs are also

potentially lower for younger men due to lower opportunity cost of time. However, when we restrict our sample to male users who are younger than the median age of male profiles on the platform, we find that these younger male users are also less likely to express an interest in a working female profile (Appendix Table A.21, Panel D).

Next, but most importantly, even after controlling for any heterogeneous effects arising from variation in the income levels of male suitors on interests received by working female profiles (Appendix Table A.12), we continue to find that upper caste male suitors are less likely to send interests to working female profiles. This drives the overall penalty faced by them. In fact, once we control for the differential effect of male incomes on interests received by working female profiles, we also find that high caste males in Bangalore are more likely to penalize working women (column 6). Finally, a prior study on a matrimonial platform by Dhar (2023) in Delhi, where invites were sent randomly by fictitious working and non-working female profiles to male profiles, also finds that men express lower interest in women who want to work after marriage. In this case, male users were responding to invites randomly sent from one of the fabricated female profiles, involving lower or zero search costs, rather than actively screening and searching for these profiles. Yet the study finds similar results. To sum up, all of the above evidence indicates that search costs cannot drive our findings.

Quality of interests: It is also possible that working women do not truly incur a penalty if the average 'quality' of interests they receive is higher even though the 'quantity' (number of male interests) is lower. If our results are driven by male suitors whose education levels or family incomes are lower than that of female profiles or whose caste categories do not match that of the female profiles, then clearly working women would not face any penalty since these are poor quality interests for them and are unlikely to have materialized into a match eventually. To test for match quality, we restrict our analysis to male suitors on the platform who have at least as much education and family income as stated for fictitious female profiles

or match the female profiles on caste. We find that working women face the interest penalty even when their education levels and family incomes are, at most, that of the male profile and within the same caste (Appendix Table A.21, Panels A – C). These results indicate that our findings are not driven by poor 'quality' of male interest for women who do not work. The observed penalty is also imposed by men who are likely to be considered 'high quality' potential matches on education and family income for a female profile.

Parental preferences and other channels: Finally, could our findings be driven solely by parental preferences and interests rather than prevailing gender attitudes among male suitors? 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.22).

Note that there could be other factors driving these results, 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 a higher threat to their safety when working outside the home. 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.

Higher social status attached by households to certain occupations, such as those where the workforce is dominated by women, could be correlated with better work-life balance in these occupations, besides other factors. The heterogeneous results by occupation may then partly reflect differential status attributed to jobs in the marriage market. However, to the extent that the social status associated with these occupations is derived from prevailing cultural preferences about acceptable jobs for women, patriarchal attitudes would remain a pertinent factor.

7 Conclusion

We conduct an online experiment that allows us to measure partner preferences of men on a digital match-making platform for marriage in India. We find that women who are currently working are 12.8% less likely to receive interest from male suitors relative to women who are currently not working. Moreover, women engaged in 'masculine' occupations are 3.3% 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 of high caste men in north India, highlighting the strong presence of patriarchal gender norms typically associated with the northern regions and upper castes in the country. Our findings suggest that expectations regarding returns in the marriage market may influence women's decisions about labor force participation and the nature of work they engage in, before marriage. Policy measures that weaken regressive gender attitudes may be key to closing gender gaps in labor force participation and reducing occupational sex segregation.

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Notes

[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).

[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)

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

[4]We define norms as the implicit and informal rules that most people accept and follow, and which govern behavior (ODI, 2024). A social norm is a collectively shared belief about what others do (what is typical) and what is expected of what others do within the group (what is appropriate) (Heise & Manji, 2016).

[5]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.

[6]This is in line with the existing literature on compensating wage differentials which finds higher wages in inflexible or more demanding jobs vis-a-vis flexible or less demanding jobs (Goldin, 2014). 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.

[7]Recent data from the NFHS-4 conducted in 2015-16 confirms these patterns. Analysis available on request.

[8]For example, Dyson & Moore (1983) hypothesize that kinship structures, such as endogamous marriage in the south, result in higher female autonomy in the region. Others such as Bardhan (1974) show that higher cultivation of rice in the south which included a greater demand for greater female labor was a contributing factor to greater value on women's labor in the south, akin to work by Alesina et al. (2013) who show that societies with greater use of plough placed higher value on male labor relative to female labor.

[9]This index is constructed using data under five broad domains: (1) domination of men over women, (2)

domination of the older generation over the younger generation, (3) patrilocality, and (4) son preference (5) socioeconomic domination. They use 12 variables across these five domains: proportion of female headed households, proportion of younger brides, proportion of wives older than the husband, younger head of household, proportion of neo-local residence among young men, incidence of joint family, proportion of married daughters living with parents, proportion of boys among the last children, sex ratio in children age 0–6 years, ideal number of sons, proportion of wives who are more educated than their husband, proportion of women of working age engaged in professional work. The index adapts and contextualizes the methodology used for the European Patriarchy Index in Gruber & Szołtysek (2016). More details can be found in Singh *et al.* (2022)

[10]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.

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

[12]Specifically, we compare the demographics of never married profiles on the platform (in September 2020, before the implementation of our experiment) with those of the never married population in India, using the PLFS (2018) data for urban India (Appendix Table A.4). We restrict the sample to women aged 18 and above and men aged 21 and above – 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. On average, men on the platform are older (30 years on the platform vs. 25.8 years in the population), more educated (88% are graduate or higher on the platform vs. 63% in the population), more likely to be employed and have higher income conditional on employment (almost four times higher than the population). The proportion of SC men is also lower on the platform as compared to the PLFS. We find similar patterns for women in Panel B – women on the platform are older, more educated and earn a higher income when employed. Even after excluding individuals currently enrolled in an educational institution (who are less likely to be active on the marriage market) in the PLFS sample, our findings remain similar.

[13]We find that older, upper caste, working and higher income earning men send larger number of total interests (Appendix Table A.5). While the effect of income is statistically insignificant, the direction broadly aligns with plausibly a higher expected response by these profiles – the existing literature shows that women value income earning potential in men (Fisman *et al.*, 2006; Hitsch *et al.*, 2010). This is likely to be greater in older, higher caste, employed men.

[14]In the PLFS 2018-19, 50% of female employees stands at $\approx$ 75th percentile and 10% of female employees stands at $\approx$ 25th percentile of the distribution of female workers. To avoid occupations which were too close

to the cut-offs 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.

[15]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.

[16]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.

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

[18]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.

[19]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.

[20]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. Further, users on the platform can also apply filters to view only profiles matching their preferred characteristics while searching for potential partners. Thus, instead of using profile views, we use the entire set of interacting male profiles to create a set of potential suitors.

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

[22]Notably, most men send interests to only working female profiles. This is because of all our fictitious female profiles 86% were employed.

[23]Panel B has lower observations than panel A since some controls are missing for male suitors.

[24]Additionally, we also control for whether the caste and education of the female profile is lower or higher than the caste and education of the male suitor and report the results in Appendix Table A.9. We find that the probability that a working woman receives lower interests remains the same. Interestingly, as discussed previously, we find almost all interests to be within the same caste since the probability that a male sends an interest to a higher caste or a lower caste female is smaller by almost 100% in Panel A (over the mean interests). On the other hand, Panel B shows that males are less likely to send an interest to females who are more educated than them by 15.8% and less educated than them by 6.3%, when compared to women who have the same education as them. This shows that male suitors on the platform value higher educated women in the marriage market as long as the education does not exceed theirs. Qualitatively, the lower probability of receiving an interest by working women is similar in magnitude to the lower probability of receiving an interest by women who are more educated than male suitors.

[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.

[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 the overall disparity between the SCs and "others" is much smaller viz-a-viz other states.

[27]Note that SC/ST caste categories belong to lower income brackets (with almost 40% lower income) than Brahmins and Other High Caste male suitors on the platform. Hence, heterogeneous findings by male caste may also reflect income heterogeneity. We have, however, controlled for male suitor income throughout our analysis.Additionally, in Appendix Table A.12 we also interact the working status of the fictitious female profile with the caste and income of the male suitor (columns 4-6). The coefficient on our main variable of

interest 'Working' which shows the differential interests shown by other high caste in working female profiles remains significantly negative even after controlling for the heterogeneous effects of suitor income. In fact, the coefficients are quite similar in magnitude with and without heterogeneous income effects. We also continue to find that Brahmin suitors display lower interests in working (W) female profiles ($W + W \times Brahmin$) while there is no penalty from scheduled caste suitors ($W + W \times SC/ST$). Results by occupation type are also stable across castes even after controlling for heterogeneous income effects (Appendix Table A.13).

[28]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).

[29]We also examine the preferences for women across occupation type by their education and that of the suitors. We find that the penalty for working in neutral and masculine occupations largely exists for women with Diploma level of education. Similarly, we find that occupational penalty reduces as suitor education increases. These results are omitted for brevity but are available on request.

[30]Nevertheless, we estimate Equations 1 and 2, keeping only female profiles that were viewed by a given male suitor since the platform allows the profile creator to track who views them. For Equation 1, we do not find any overall significant difference in interest received by working status of female profiles. However, in line with our hypothesis of gender attitudes being more regressive for higher castes, we find that higher caste male suitors are less likely to send interests to working female profiles (Appendix Table A.16). We also report the estimates of Equation 2 in Appendix Table A.17. Conditional on viewing a female profile, we continue to find that women working in 'masculine' or 'neutral' occupations are less likely to receive interests when compared to women in 'feminine' occupations. Further, heterogeneity by caste of the interacting male suitor shows that these results are driven by higher castes in Delhi (Appendix Table A.18).
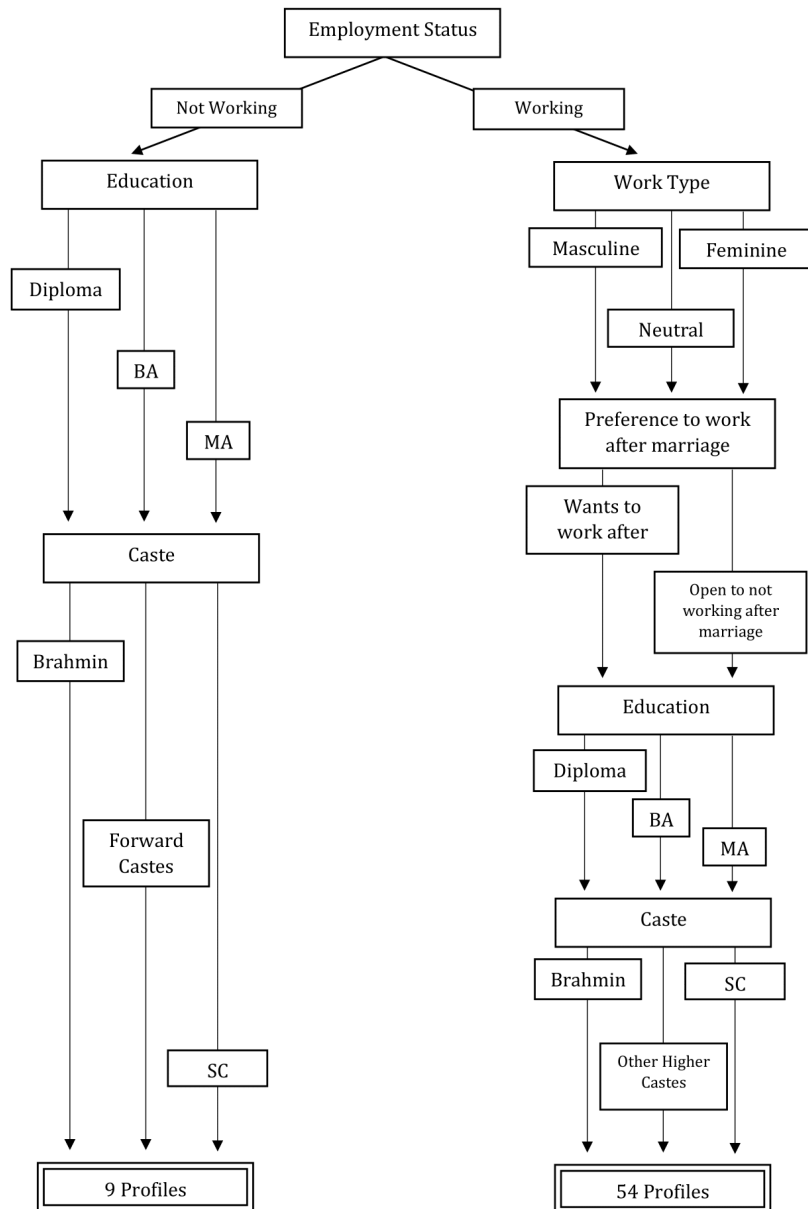
Figure 1: Female Profile Creation on the Platform

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 work status, type, preference to work after marriage, caste and education for the fictitious female profiles.

Table 2: Effect of Female Work Status on Male Interest

	(1)	(2)	(3)
	Overall	Delhi	Bangalore
Panel A: Without male suitor controls			
Working	−0.008***	−0.010***	−0.002
	(0.001)	(0.002)	(0.004)
Observations	338058	272916	65142
Mean Y	0.062	0.058	0.077
Mean Y (NW)	0.069	0.067	0.078
Panel B: With male suitor controls			
Working	−0.009***	−0.010***	−0.002
	(0.001)	(0.002)	(0.004)
Observations	329427	265545	63882
Mean Y	0.062	0.059	0.078
Mean Y (NW)	0.070	0.067	0.079
Controls			
City FE	✓		
Caste FE		✓	✓
City × Caste FE	✓		
Education 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 fictitious female profile who is currently employed and zero otherwise. 'Mean Y' shows the average value of the dependent variable across all female profiles whereas **'Mean Y (NW)'** shows the average value of the dependent variable for female profiles which are **not working**. Fixed effects reflect controls for female profile characteristics; male profile controls include 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. Missing values for some male suitor characteristics lead to lower observations in Panel B. Standard errors clustered at the level of the male (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
Panel A: Without male suitor controls			
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)
Observations	338058	272916	65142
Mean Y	0.062	0.058	0.077
Mean Y (F)	0.061	0.058	0.075
Masculine=Neutral	[0.061]	[0.101]	[0.367]
Panel B: With male suitor controls			
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)
Observations	329427	265545	63882
Mean Y	0.062	0.059	0.078
Mean Y (F)	0.062	0.059	0.075
Masculine=Neutral	[0.057]	[0.104]	[0.316]
Controls			
City FE	✓		
Caste FE		✓	✓
City × Caste FE	✓		
Education 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 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. 'Mean Y' shows the average value of the dependent variable across all female profiles whereas **'Mean Y (F)'** shows the average value of the dependent variable for female profiles which are working in **'feminine'** occupations. Fixed effects reflect controls for female profile characteristics; male profile controls include 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. Missing values for some male suitor characteristics lead to lower observations in Panel B. Standard errors clustered at the level of the male (suitor) profile in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. p-values reported in square brackets.

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)
Observations	282366	227610	54756
Mean Y	0.061	0.057	0.077
Mean Y (F)	0.062	0.059	0.075
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			
City FE	✓		
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. 'Mean Y' shows the average value of the dependent variable across all female profiles whereas **'Mean Y (F)'** shows the average value of the dependent variable for female profiles which are working in **'feminine'** occupations. Fixed effects reflect controls for female profile characteristics; male profile controls include 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 male (suitor) profile in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. p-values reported in square brackets.

Table 5: Effect of Female Work Status on Male Interest: Robustness (Suitor Fixed Effects)

	(1)	(2)	(3)
	Overall	Delhi	Bangalore
Working	−0.008***	−0.010***	−0.002
	(0.001)	(0.002)	(0.004)
Observations	338058	272916	65142
Mean Y	0.062	0.058	0.077
Mean Y (NW)	0.069	0.067	0.078
Controls			
City FE	✓		
Caste FE		✓	✓
City × Caste FE	✓		
Education FE	✓	✓	✓
Male Suitor 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 fictitious female profile who is currently employed and zero otherwise. 'Mean Y' shows the average value of the dependent variable across all female profiles whereas **'Mean Y (NW)'** shows the average value of the dependent variable for female profiles which are **not working**. Fixed effects reflect controls for female profile characteristics. All regressions control for fixed effects for the engaging male profiles. This leads to an increase in observations since male profile control variables have missing values for some profiles in Table 2. Standard errors clustered at the level of the male (suitor) profile in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 6: Effect of Female Occupation Type on Male Interest: Robustness (Suitor Fixed Effects)

	(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)
Observations	338058	272916	65142
Mean Y	0.062	0.058	0.077
Mean Y (F)	0.061	0.058	0.075
Masculine=Neutral	[0.061]	[0.101]	[0.367]
Controls			
City FE	✓		
Caste FE		✓	✓
City × Caste FE	✓		
Education FE	✓	✓	✓
Male Suitor 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 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. 'Mean Y' shows the average value of the dependent variable across all female profiles whereas **'Mean Y (F)'** shows the average value of the dependent variable for female profiles which are working in **'feminine'** occupations. Fixed effects reflect controls for female profile characteristics. All regressions control for fixed effects for the engaging male profiles. This leads to an increase in observations since male profile control variables have missing values for some profiles in Table 3. Standard errors clustered at the level of the male (suitor) profile in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. p-values reported in square brackets.

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 Castes
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
Mean Y (NW)	0.070	0.077	0.083	0.049
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	0.059	0.063	0.069	0.044
Mean Y (NW)	0.067	0.076	0.084	0.043
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	0.078	0.090	0.078	0.065
Mean Y (NW)	0.079	0.081	0.082	0.075
Controls				
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. Fixed effects reflect controls for female profile characteristics; male profile controls include 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. 'Mean Y' shows the average value of the dependent variable across all female profiles whereas **'Mean Y (NW)'** shows the average value of the dependent variable for female profiles which are **not working**, overall and by caste across columns. In addition to the FE mentioned at the end of the table, Panel A also contains City FE (of the fictitious female profile). Standard errors clustered at the level of the male (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 Male Suitors)

	(1)	(2)	(3)	(4)
	Overall	Brahmin	Other High Castes	Scheduled Castes
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	0.062	0.058	0.065	0.053
Mean Y (NW)	0.070	0.066	0.074	0.049
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	0.059	0.056	0.060	0.053
Mean Y (NW)	0.067	0.067	0.070	0.049
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	0.078	0.068	0.083	0.053
Mean Y (NW)	0.079	0.064	0.087	0.051
Controls				
Education FE	✓	✓	✓	✓
Caste 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 male profile. Fixed effects reflect controls for female profile characteristics; male profile controls include 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. 'Mean Y' shows the average value of the dependent variable across all female profiles whereas **'Mean Y (NW)'** shows the average value of the dependent variable for female profiles which are **not working**, overall and by caste across columns. In addition to the Fixed Effects mentioned at the end of the table, Panel A also contains City and Caste X City FE (corresponding to the female profile). Standard errors clustered at the level of the male (suitor) profile in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

A Online Appendix

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

(a) Labor market (TUS)

(b) Domestic work (TUS)

(c) Labor market (CPHS)

(d) Domestic work (CPHS)
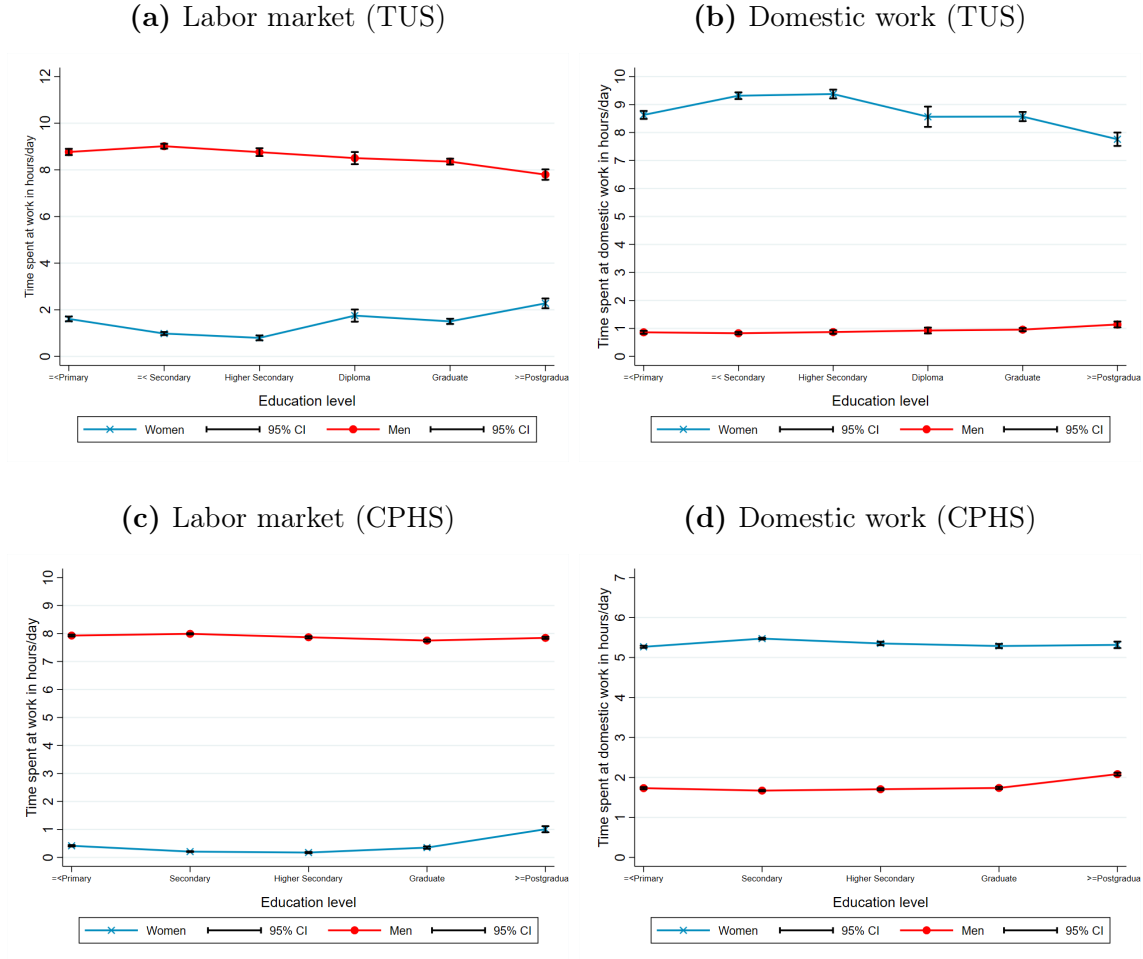
Notes: Figures (a) and (c) plot the average time spent per day (hours) in the labor market by gender and education. Figures (b) and (d) plot the average time spent per day (hours) in domestic work (household chores) by gender and education. The sample includes urban married women and men aged 20-45 years.
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).
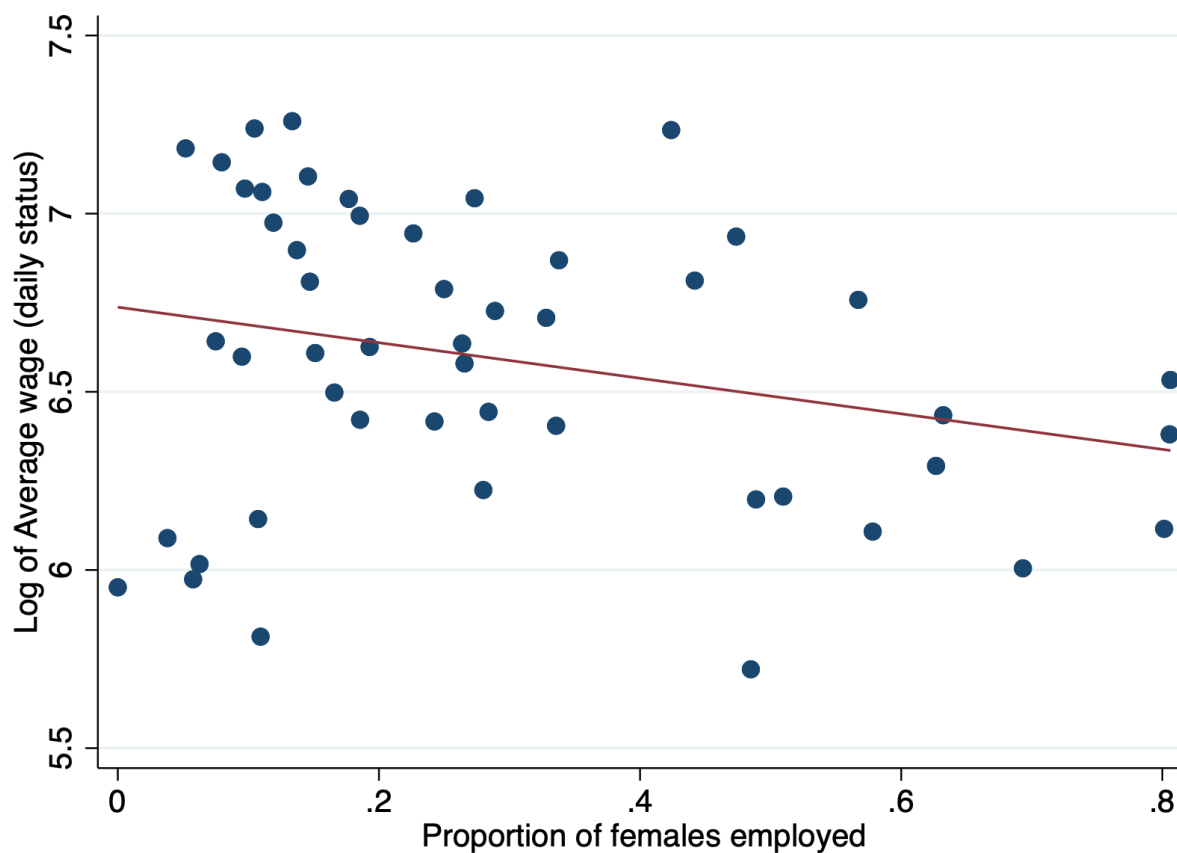
Figure A.2: Returns to Education by Gender
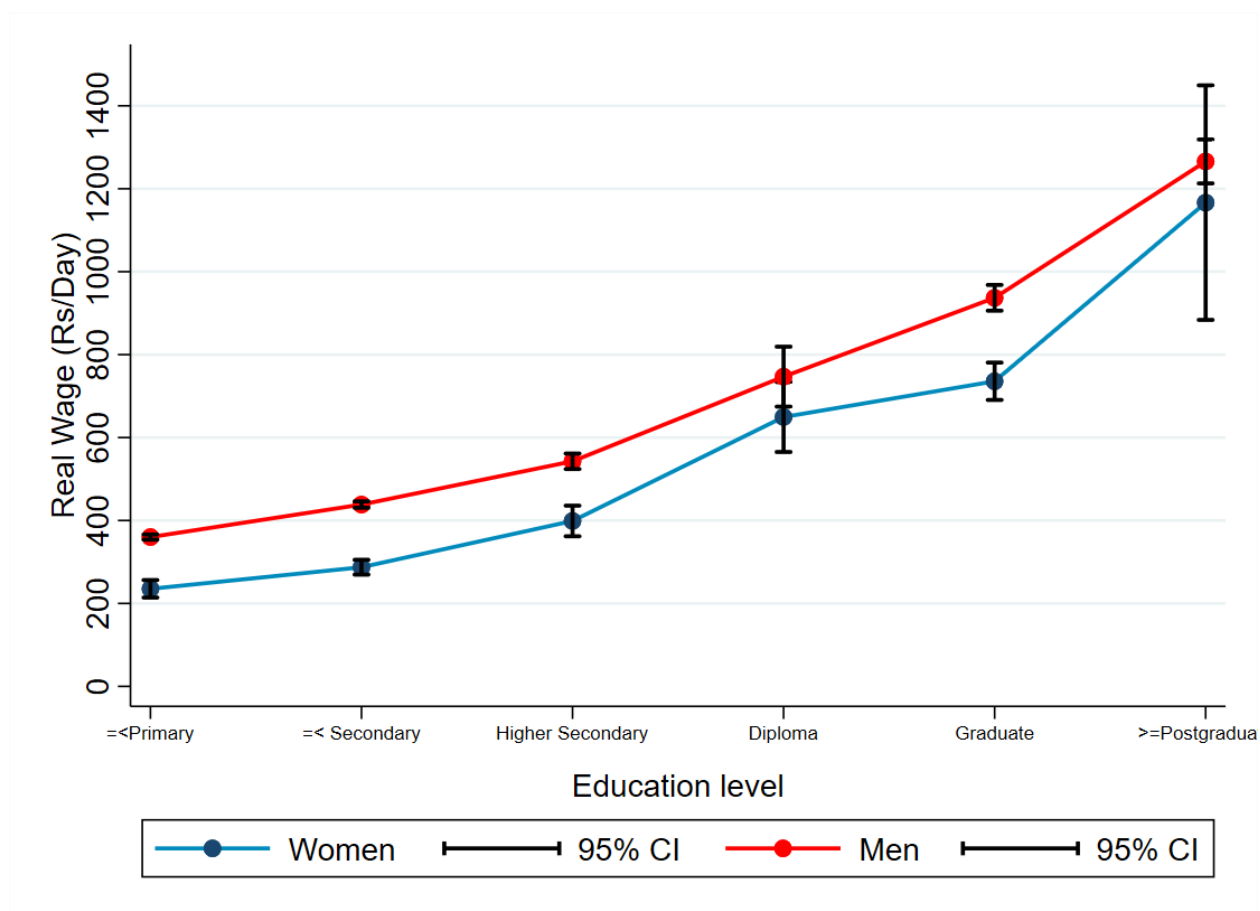
Notes: The figure plots average daily wage rates for employed individuals in paid employment (salaried or casual) by gender and education. The sample includes individuals aged 20-45 years in urban India.
*Source:* Periodic Labor Force Survey, 2018-19.

Figure A.3: 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. The correlation coefficient between the two variables is -0.2502 ($p=0.0830$).
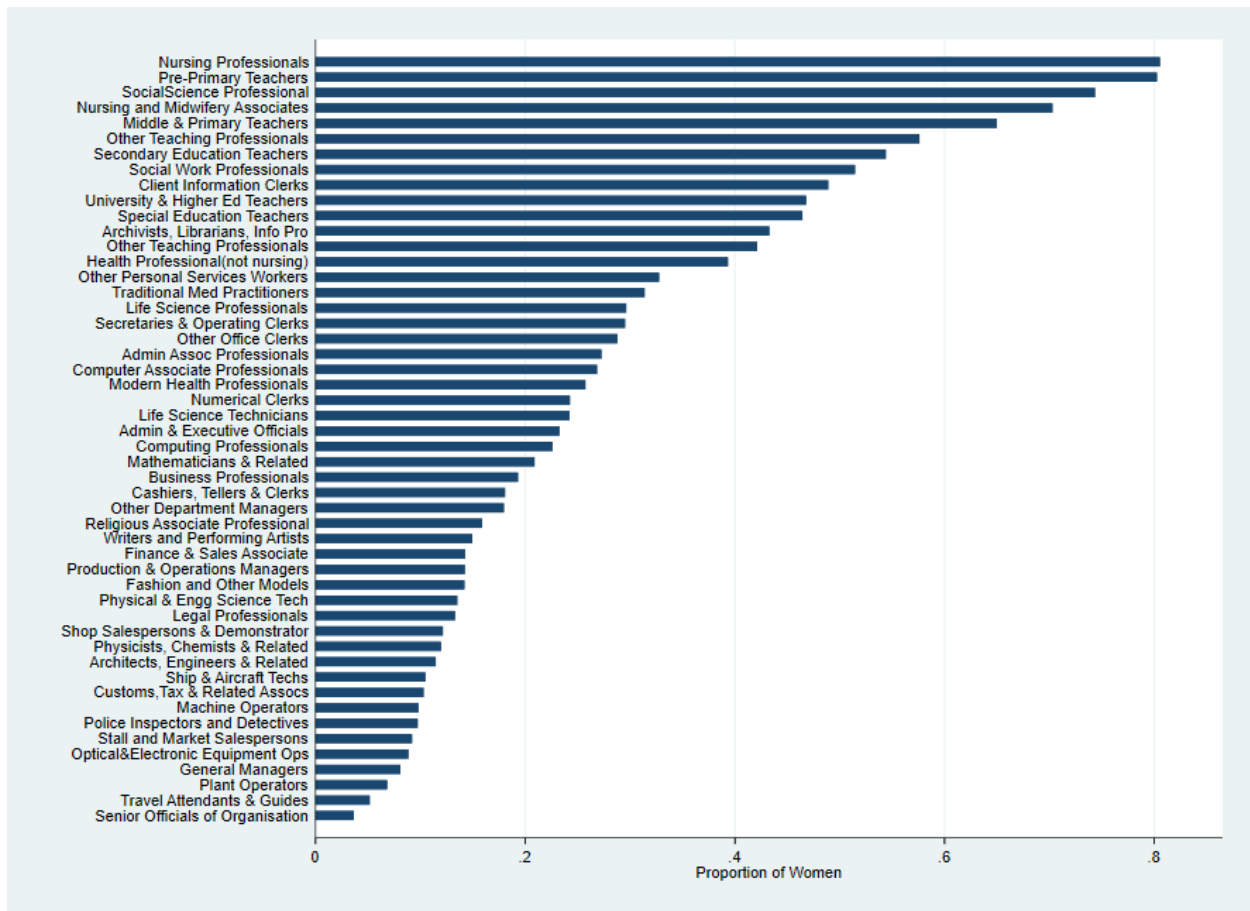*Source:* Periodic Labor Force Survey, 2018-19.

Figure A.4: Patriarchy Index and the Proportion of Time Spent by Women in Domestic Work
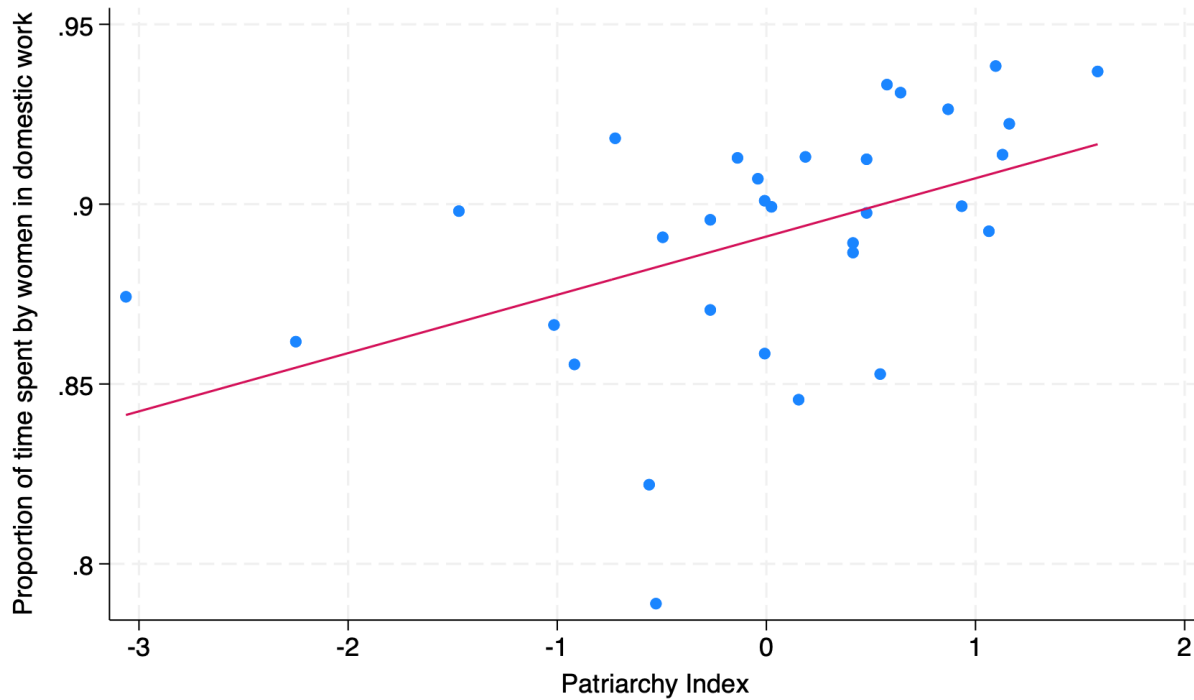
Notes: The figure shows the scatter plot between the proportion of average time spent by women in a state in domestic work out of the total (average) time spent in domestic work by both men and women in that state and the state level Patriarchy Index. The correlation between the two variables is 0.472 (p=0.006). *Source:* Singh *et al.* (2022) for the state level Patriarchy Index based on the NFHS, 2015-16 data and Time Use Survey (TUS), 2019.
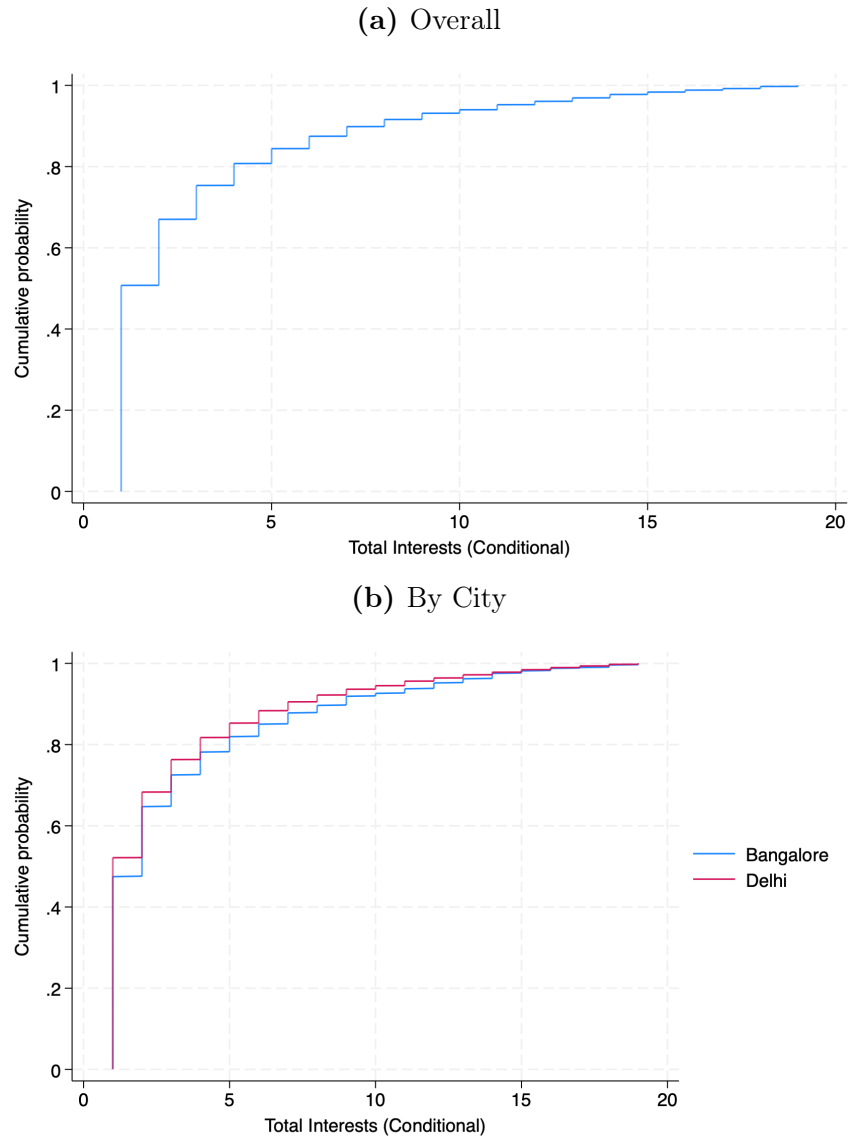
Figure A.5: Women's Occupational Distribution

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.

Figure A.6: CDF of Total Interests Sent by Male Suitors on Platform

(a) Overall

(b) By City

Notes: Figures (a) and (b) plot the overall and by city distribution of total interests sent by male suitors to our fictitious female profiles, respectively. The analysis is conducted for male suitors who expressed interest in at least one of our female profiles.

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)
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 (by Occupation)

	All Education		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)
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 $\approx$ 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 and Caste)

Sample	All Education		Completed Schooling	
	Domestic	Market	Domestic	Market
Panel A: Heterogeneity by North-South				
Female	5.573***	−5.820***	5.349***	−5.762***
	(0.044)	(0.054)	(0.066)	(0.085)
North	−0.496***	−0.011	−0.614***	−0.028
	(0.058)	(0.047)	(0.087)	(0.077)
Female × North	0.504***	−0.839***	0.609***	−0.581***
	(0.060)	(0.069)	(0.092)	(0.110)
Observations	46181	46177	19968	19968
Other Controls	✓	✓	✓	✓
Panel B: Heterogeneity by Caste				
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)
Observations	63964	64058	27248	27301
Controls				
State FE	✓	✓	✓	✓
Other Controls	✓	✓	✓	✓

Notes: The dependent variable is the log of daily time spent on domestic work for the first and third columns, and the log of daily time spent at work for the second and fourth columns. 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. Panel A includes select states – the northern states include Gujarat, Rajasthan, Uttar Pradesh, Madhya Pradesh, Punjab, Haryana, and Delhi while the southern states include Kerala, Tamil Nadu, Andhra Pradesh, Telangana, Karnataka, and Maharashtra. Panel B includes data from all states, leading to higher number of observations. 'High Caste' is an indicator that takes value one if the person belongs to 'Other High Caste (including Brahmins)' or 'Other Backward Classes' and zero otherwise. Controls include age, age squared, education, caste, religion, household MPCE decile and number of children aged between 0 to 5 years. In Panel A we do not control for state or district fixed effects since the main objective is to examine regional differences. Regressions are weighted using sample 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: Characteristics of Men and Women: Platform vs National Sample

	Platform	PLFS	PLFS (Non-students)
	(1)	(2)	(3)

Panel A : Men			
Age (Years)	30.156	25.772	26.876
Scheduled Caste/Tribe	0.058	0.146	0.146
Employed	0.971	0.507	0.668
Annual Income ('00000 INR)	9.204	2.194	2.209
Highest Level of Education			
High School/Diploma	0.114	0.375	0.304
Bachelors	0.548	0.510	0.550
Masters and Above	0.338	0.115	0.146
Observations	214832	6370	4739

Panel B : Women			
Age	28.784	22.502	25.328
Scheduled Caste/Tribe	0.067	0.160	0.155
Employed	0.741	0.192	0.418
Annual Income	6.106	2.065	2.136
Highest Level of Education			
High School/Diploma	0.041	0.503	0.228
Bachelors	0.457	0.382	0.541
Masters and Above	0.502	0.115	0.231
Observations	189727	5436	2388

Notes: Column (1) shows the mean years of age, percentage scheduled caste/tribe, percentage employed, average annual income ('00000 INR) and the education distribution of urban Hindu never-married men (Panel A) and women (Panel B) on the matrimonial platform. The income is calculated by taking the mid-point of the range of income values reported for a profile on the matrimonial portal. Reported caste on the platform was matched with state caste lists to classify them as scheduled castes. Similar statistics from the nationally representative PLFS (2018-19), weighted using sampling weights, are presented in columns (2)-(3) after keeping Hindu, never-married individuals aged >17 for women and >20 (based on platform's age criteria) for men who have at least schooling education in urban India. This also aligns with the legal age for marriage for women and men in India. Column (3) additionally drops people currently enrolled in educational institutes in the PLFS. Annual income is calculated for the subset of men and women in this sample who report working in the labor market (includes paid workers and self-employed). The PLFS sample size corresponds to the unweighted counts of unique individuals meeting the aforementioned criteria in each column.
Source: Periodic Labor Force Survey (2018-19) across all states of India; Platform data (September 2020).

Table A.5: Total Interests Sent by Male Suitors to Fictitious Female Profiles

	(1)	(2)	(3)
	Overall	Delhi	Bangalore
Age (Years)	0.140***	0.121***	0.007
	(0.035)	(0.034)	(0.077)
Height (Inches)	0.002	−0.002	−0.011
	(0.029)	(0.025)	(0.085)
Income ('00000 INR)	0.005	0.007	0.006
	(0.012)	(0.012)	(0.030)
Employed	1.389***	1.432***	0.118
	(0.325)	(0.266)	(1.803)
Caste Category			
Brahmin	−0.238	−0.174	−0.492
	(0.225)	(0.213)	(0.571)
SC/ST	−0.872***	−0.377	−2.482***
	(0.312)	(0.339)	(0.642)
Profile Manager			
Managed by Parents/Relative	−0.568***	−0.534***	−0.287
	(0.208)	(0.194)	(0.653)
Managed by Others	0.203	0.085	0.594
	(1.166)	(1.047)	(2.409)
Education			
Bachelors	−0.581	−0.115	−2.129**
	(0.363)	(0.307)	(0.936)
Masters and above	−0.170	0.075	−1.018
	(0.394)	(0.346)	(0.968)
Other degree	−0.623	0.001	−2.489**
	(0.620)	(0.592)	(1.134)
Observations	4690	3962	938
Mean Y	4.1610	3.7398	4.9968
R-squared	0.027	0.029	0.068
Controls			
Suitor State FE	✓	✓	✓

Notes: The dependent variable is total number of interests sent by a male profile to the created fictitious female profiles on the platform. Since we only observe the behavior of male profiles who have sent at least one interest to our female profiles, this analysis is conditional on a male profile sending an interest. It is regressed on characteristics of the male profiles captured on the platform like age, height, income ('00000 INR), whether currently employed, caste, profile manager, education degree and state of residence. The omitted category for caste is 'Other High Caste', for profile manager is 'Managed by Self' and for education is 'High School / Diploma'. We keep a unique set of male profiles who interact with any of the fictitious female profiles across cities in column (1), with Delhi based female profiles (column 2) and with Bangalore based female profiles (column 3). The observations across columns (2) and (3) will not add up to that in column (1) since a male suitor can send interests to both Delhi and Bangalore based female profiles. In this case the male suitor will be included once in column (1) but included both in columns (2) and (3). Standard errors are robust and corrected for heteroscedasticity. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A.6: Profile Characteristics on Platform (by Gender)

	Overall			Female			Male		
	Mean	SD	N	Mean	SD	N	Mean	SD	N
Personal Characteristics									
Age (Years)	30.30	5.68	576889	29.51	5.31	269117	30.99	5.89	307772
Height (Inches)	64.32	3.77	576801	62.61	3.24	269080	65.81	3.55	307721
Income ('00000 INR)	10.37	16.88	485915	7.65	13.05	188011	12.09	18.69	297904
Employed	0.86	0.35	570949	0.73	0.44	266587	0.97	0.18	304362
Caste Category									
Brahmin	0.19	0.39	485048	0.19	0.39	224960	0.19	0.39	260088
Other High Castes	0.75	0.43	485048	0.74	0.44	224960	0.75	0.43	260088
SC/ST	0.06	0.24	485048	0.07	0.25	224960	0.06	0.23	260088
Profile Manager									
Parents/Relative	0.42	0.49	576889	0.58	0.49	269117	0.28	0.45	307772
Self	0.57	0.49	576889	0.41	0.49	269117	0.71	0.45	307772
Others	0.01	0.08	576889	0.01	0.07	269117	0.01	0.08	307772
Highest Level of Edu.									
High School/Diploma	0.10	0.29	576889	0.06	0.24	269117	0.13	0.33	307772
Bachelors	0.48	0.50	576889	0.44	0.50	269117	0.51	0.50	307772
Masters and above	0.39	0.49	576889	0.46	0.50	269117	0.32	0.47	307772
Other degree	0.04	0.20	576889	0.04	0.19	269117	0.05	0.21	307772

Notes: The table reports the average characteristics for male and female profiles active on the platform in September 2020, across all states of India. Income is calculated by taking the mid point of the range of income value declared on the platform. For unemployed males the income is zero. The caste group is assigned based on the caste category provided on the platform, which was matched with state caste lists to classify profiles as Scheduled Caste. Age, profile manager, education are mandatory fields but the others are optional and hence have missing data for some profiles leading to smaller observations for them.

Table A.7: Engaging Male Suitor Characteristics

	Overall			Delhi			Bangalore		
	Mean	SD	N	Mean	SD	N	Mean	SD	N
Personal Characteristics									
Age (Years)	29.105	3.141	5140	28.926	3.107	4332	30.146	3.190	1034
Height (Inches)	65.972	3.405	5140	65.950	3.411	4332	66.060	3.370	1034
Income ('00000 INR)	9.077	12.754	5010	8.869	12.244	4215	9.860	13.998	1014
Employed	0.968	0.177	5135	0.965	0.183	4327	0.981	0.138	1034
Caste Category									
Brahmin	0.226	0.418	5140	0.235	0.424	4332	0.191	0.393	1034
Other High Castes	0.685	0.465	5140	0.678	0.467	4332	0.715	0.452	1034
SC/ST	0.089	0.285	5140	0.087	0.281	4332	0.095	0.293	1034
Profile Manager									
Managed by Parents/Relative	0.289	0.453	5140	0.303	0.460	4332	0.209	0.407	1034
Managed by himself	0.702	0.457	5140	0.688	0.463	4332	0.783	0.412	1034
Managed by Others	0.008	0.091	5140	0.009	0.092	4332	0.008	0.088	1034
Highest Level of Edu.									
High School/Diploma	0.149	0.356	5140	0.145	0.353	4332	0.173	0.379	1034
Bachelors	0.525	0.499	5140	0.528	0.499	4332	0.488	0.500	1034
Masters and above	0.279	0.448	5140	0.282	0.450	4332	0.276	0.447	1034
Other degree	0.048	0.213	5140	0.045	0.206	4332	0.063	0.243	1034

Notes: The table reports the average characteristics of 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 profile on the portal. For unemployed males the income is zero. The caste group is assigned based on the caste declared on the platform after matching with the state caste lists to classify profiles as Scheduled Caste. 4332 and 1034 male profiles expressed an interest for at least one fictitious female profile posted in Delhi and Bangalore, respectively. Age, profile manager, education are mandatory fields but the others are optional and hence have missing data for some profiles leading to smaller observations for them.

Table A.8: Comparison of Male Suitor Characteristics (by Interest Type)

	(1) Only NW	(2) Only W	(3) Both	(4) 1-3	(5) 2-3	(6) 2-1
Age (Years)	29.397	28.967	29.381	0.017	-0.414***	-0.430***
	(3.264)	(3.098)	(3.187)	(0.169)	(0.108)	(0.150)
Height (Inches)	65.705	65.972	66.096	-0.390**	-0.123	0.267*
	(3.252)	(3.464)	(3.288)	(0.171)	(0.113)	(0.152)
Income ('00000 INR)	8.060	9.091	9.509	-1.449**	-0.418	1.031*
	(13.368)	(12.314)	(13.696)	(0.710)	(0.459)	(0.620)
Employed	0.974	0.963	0.978	-0.004	-0.015***	-0.011
	(0.160)	(0.188)	(0.146)	(0.008)	(0.005)	(0.008)
Caste						
Brahmin	0.207	0.226	0.235	-0.028	-0.009	0.019
	(0.406)	(0.418)	(0.424)	(0.022)	(0.014)	(0.019)
Other High Castes	0.733	0.674	0.693	0.040*	-0.019	-0.059***
	(0.443)	(0.469)	(0.461)	(0.023)	(0.016)	(0.021)
SC/ST	0.060	0.100	0.072	-0.012	0.027***	0.040***
	(0.237)	(0.300)	(0.259)	(0.013)	(0.009)	(0.011)
Profile Manager						
Managed by himself	0.701	0.702	0.703	-0.002	-0.001	0.001
	(0.458)	(0.457)	(0.457)	(0.024)	(0.016)	(0.021)
Managed by Parents/Relative	0.282	0.290	0.290	-0.009	-0.000	0.008
	(0.450)	(0.454)	(0.454)	(0.024)	(0.015)	(0.021)
Managed by Others	0.017	0.008	0.006	0.011*	0.002	-0.009
	(0.129)	(0.088)	(0.078)	(0.006)	(0.003)	(0.006)
Education						
High School/Diploma	0.213	0.135	0.161	0.052**	-0.026**	-0.078***
	(0.410)	(0.342)	(0.368)	(0.021)	(0.012)	(0.019)
Bachelors	0.493	0.530	0.523	-0.031	0.007	0.038
	(0.500)	(0.499)	(0.500)	(0.026)	(0.017)	(0.023)
Masters and above	0.224	0.289	0.272	-0.048**	0.017	0.065***
	(0.417)	(0.453)	(0.445)	(0.022)	(0.015)	(0.020)
Other degree	0.071	0.045	0.043	0.027**	0.002	-0.025**
	(0.257)	(0.208)	(0.204)	(0.013)	(0.007)	(0.012)
Observations	536	3454	1150	1686	4604	3990

Notes: The table shows mean characteristics of the male suitors in our data by three categories of interests displayed by them towards female profiles: Column (1) comprises of male suitors who only sent interests to **not working (NW)** female profiles; Column (2) comprises of male suitors who only sent interests to **working (W)** female profiles; and column (3) comprises of male suitors who sent interests to both not working and working female profiles. The characteristics of male suitors that we consider are: age, height, income ('00000 INR), employment status (indicator variable for whether currently employed), caste category, profile manager (self/parent/managed by others), and highest level of education. We compare the difference in the distribution of these characteristics between columns (1) vs (3), (2) vs (3) and (2) vs (1), in columns (4), (5) and (6), respectively. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A.9: Effect of Female Work Status on Male Interests: Robustness (Additional Controls)

	(1)	(2)	(3)
	Overall	Delhi	Bangalore
Panel A : Higher Caste			
Working	–0.009***	–0.010***	–0.002
	(0.001)	(0.002)	(0.004)
Lower Female Caste	–0.063***	–0.064***	–0.060***
	(0.003)	(0.003)	(0.008)
Higher Female caste	–0.084***	–0.087***	–0.072***
	(0.004)	(0.004)	(0.010)
Observations	329427	265545	63882
Mean Y	0.062	0.059	0.078
Mean Y (NW)	0.070	0.067	0.079
Panel B : Higher Education			
Working	–0.008***	–0.010***	0.001
	(0.002)	(0.002)	(0.004)
Less educated female	–0.004**	–0.005***	0.001
	(0.002)	(0.002)	(0.005)
More educated female	–0.010***	–0.009***	–0.012**
	(0.002)	(0.002)	(0.005)
Observations	314244	254205	60039
Mean Y	0.063	0.059	0.079
Mean Y (NW)	0.069	0.067	0.078
Controls			
City FE	✓		
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. 'Working' an indicator variable that takes a value of one for a fictitious female profile who is currently employed and zero otherwise. Panel A additionally controls for whether the caste of the fictitious female profile is lower or higher than the caste of the male suitor. 'Lower Female Caste' ('Higher Female caste') takes a value of one if the caste of the fictitious female profile is lower (higher) than the caste of the male suitor. The caste hierarchy is Brahmin > Other High Caste > SC. Similarly, Panel B controls for whether the education of the fictitious female profile is lower or higher than the education of the male suitor. 'Lower Female Education' ('Higher Female Education') takes a value of one if the education of the fictitious female profile is lower (higher) than the education of the male suitor. Fixed effects reflect controls for female profile characteristics; male profile controls include 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. 'Mean Y' shows the average value of the dependent variable across all female profiles whereas 'Mean Y (NW)' shows the average value of the dependent variable for female profiles which are **not working**. Standard errors clustered at the level of the male (suitor) profile in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A.10: Effect of Female Occupation Type on Male Interest (by Female Caste)

	(1)	(2)	(3)	(4)
	Overall	Brahmin	Other High Castes	Scheduled Caste
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	0.062	0.068	0.071	0.048
Mean Y (F)	0.062	0.068	0.069	0.048
Controls				
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	0.059	0.063	0.069	0.044
Mean Y (F)	0.059	0.061	0.069	0.045
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	0.078	0.090	0.078	0.065
Mean Y (F)	0.075	0.097	0.069	0.061
Controls				
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 employed in a masculine occupation and zero otherwise; 'Working - Neutral' takes a value of one if a fictitious female profile is employed 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. 'Mean Y' shows the average value of the dependent variable across all female profiles whereas 'Mean Y (F)' shows the average value of the dependent variable for female profiles which are working in **'feminine'** occupations. Fixed effects reflect controls for female profile characteristics; male profile controls include 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 male (suitor) profile in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A.11: Effect of Female Occupation Type on Male Interest (by Caste of Male Suitors)

	(1)	(2)	(3)	(4)
	Overall	Brahmin	Other High Castes	Scheduled Castes
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)
Controls				
Observations	329427	75159	225351	28917
Mean Y	0.062	0.058	0.065	0.053
Mean Y (F)	0.062	0.058	0.065	0.052
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
Mean Y (F)	0.059	0.055	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
Mean Y (F)	0.075	0.070	0.081	0.048
Controls				
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. 'Mean Y' shows the average value of the dependent variable across all female profiles whereas 'Mean Y (F)' shows the average value of the dependent variable for female profiles which are working in **'feminine'** occupations. Fixed effects reflect controls for female profile characteristics; male profile controls include 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 male (suitor) profile in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A.12: Effect of Female Work Status on Male Interests (by Male Caste): Robustness

	(1)	(2)	(3)	(4)	(5)	(6)
	Overall	Delhi	Bangalore	Overall	Delhi	Bangalore
Working (W)	−0.010***	−0.011***	−0.004	−0.012***	−0.012***	−0.012**
	(0.002)	(0.002)	(0.004)	(0.002)	(0.002)	(0.005)
Brahmin	−0.006	−0.003	−0.022**	−0.007	−0.003	−0.022*
	(0.004)	(0.005)	(0.011)	(0.004)	(0.005)	(0.011)
SC/ST	−0.024***	−0.021***	−0.034**	−0.024***	−0.021***	−0.035**
	(0.006)	(0.007)	(0.015)	(0.006)	(0.007)	(0.015)
Working × Brahmin	0.000	−0.001	0.009	0.000	−0.001	0.008
	(0.003)	(0.004)	(0.009)	(0.003)	(0.004)	(0.009)
Working × SC/ST	0.014***	0.016***	0.006	0.015***	0.016***	0.008
	(0.005)	(0.005)	(0.012)	(0.005)	(0.005)	(0.012)
Income	−0.000	0.000	−0.000	−0.000	−0.000	−0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Working × Income				0.000*	0.000	0.001***
				(0.000)	(0.000)	(0.000)
Observations	329427	265545	63882	329427	265545	63882
Mean Y	0.062	0.059	0.078	0.062	0.059	0.078
Mean Y (NW)	0.070	0.067	0.079	0.070	0.067	0.079
W + W × Brahmin	−0.010	−0.013	0.005	−0.012	−0.013	−0.004
	[0.00]	[0.00]	[0.52]	[0.00]	[0.00]	[0.58]
W + W × SC/ST	0.004	0.005	0.002	0.003	0.005	−0.004
	[0.33]	[0.31]	[0.84]	[0.54]	[0.34]	[0.73]
Controls						
City FE	✓			✓		
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' (W) is an indicator variable that takes a value of one for a fictitious female profile who is currently employed and zero otherwise. We further interact 'Working' with caste of the male suitor to estimate the heterogeneous penalty on working female profiles by caste of the male suitor, using other high castes as the base category. The coefficient of working shows the differential interests shown in working female profiles by other high caste male suitors. To arrive at the differential rates of interest from Brahmin suitors we add the coefficient on working and the interaction of working with Brahmin (W + W × Brahmin). Similarly, W + W × SC/ST shows the overall effect from male suitors belonging to scheduled castes and tribes towards working female profiles. p-value of the estimated coefficient for each caste is provided in square brackets below the estimate. 'Mean Y' shows the average value of the dependent variable across all female profiles whereas 'Mean Y (NW)' shows the average value of the dependent variable for female profiles which are **not working**. Fixed effects reflect controls for female profile characteristics; male profile controls include male profile's highest level of education, age, height, profile manager (self/parent/managed by others), and whether income is less than that of the corresponding fictitious female profile. Standard errors clustered at the level of the male (suitor) profile in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. p-values reported in square brackets.

Table A.13: Effect of Female Occupation Type on Male Interests (by Male Caste): Robustness

	(1)	(2)	(3)	(4)	(5)	(6)
	Overall	Delhi	Bangalore	Overall	Delhi	Bangalore
Masculine	−0.002*	−0.003**	0.002	−0.002	−0.003*	0.001
	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.003)
Neutral	−0.001	−0.002	0.005*	−0.002	−0.003**	0.003
	(0.001)	(0.001)	(0.003)	(0.001)	(0.002)	(0.003)
Not Working (NW)	0.009***	0.010***	0.006	0.011***	0.010***	0.014**
	(0.002)	(0.002)	(0.005)	(0.002)	(0.002)	(0.006)
Brahmin	−0.006*	−0.005	−0.010	−0.006*	−0.005	−0.010
	(0.003)	(0.003)	(0.009)	(0.003)	(0.003)	(0.009)
SC/ST	−0.012**	−0.007	−0.031***	−0.012**	−0.007	−0.031***
	(0.005)	(0.006)	(0.009)	(0.005)	(0.006)	(0.009)
Masculine × Brahmin	−0.001	0.000	−0.004	−0.001	0.000	−0.004
	(0.002)	(0.002)	(0.006)	(0.002)	(0.002)	(0.006)
Neutral × Brahmin	−0.001	0.001	−0.007	−0.001	0.001	−0.008
	(0.002)	(0.002)	(0.006)	(0.002)	(0.002)	(0.006)
NW × Brahmin	−0.001	0.002	−0.013	−0.001	0.002	−0.012
	(0.004)	(0.004)	(0.009)	(0.004)	(0.004)	(0.009)
Masculine × SC/ST	0.001	0.001	0.002	0.001	0.001	0.003
	(0.003)	(0.003)	(0.005)	(0.003)	(0.003)	(0.005)
Neutral × SC/ST	0.006*	0.005	0.008	0.006**	0.006	0.009
	(0.003)	(0.003)	(0.006)	(0.003)	(0.003)	(0.006)
NW × SC/ST	−0.012**	−0.014**	−0.003	−0.012**	−0.014**	−0.004
	(0.005)	(0.006)	(0.012)	(0.005)	(0.006)	(0.012)
Income	−0.000	0.000	−0.000	−0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Masculine × Income				−0.000	−0.000	0.000
				(0.000)	(0.000)	(0.000)
Neutral × Income				0.000*	0.000	0.000
				(0.000)	(0.000)	(0.000)
NW × Income				−0.000	0.000	−0.001**
				(0.000)	(0.000)	(0.000)
Observations	329427	265545	63882	329427	265545	63882
Mean Y	0.062	0.059	0.078	0.062	0.059	0.078
Mean Y (F)	0.062	0.059	0.075	0.062	0.059	0.075
Controls						
City FE	✓			✓		
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 (NW)' 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 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. We further interact each of the main explanatory variables with caste of the male suitor to estimate the heterogeneous penalty on female profiles based on their education by caste, using other high castes as the base category. The coefficient of 'Masculine', 'Neutral' and 'Not working' show the differential interests shown in female profiles based on their occupation status vs female profiles in 'feminine' occupations by other high caste male suitors. To arrive at the differential rates of interest from Brahmin and SC/ST suitors we add the coefficient on each of these explanatory variables and the coefficient on the interaction of the same explanatory variables with Brahmin and SC/ST caste categories. 'Mean Y' shows the average value of the dependent variable across all female profiles whereas '**Mean Y (F)**' shows the average value of the dependent variable for female profiles which are working in '**feminine**' occupations. Fixed effects reflect controls for female profile characteristics; male profile controls include male profile's highest level of education, age, height, profile manager (self/parent/managed by others), and whether income is less than that of the corresponding fictitious female profile. Standard errors clustered at the level of the male (suitor) profile in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A.14: 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	0.062	0.058	0.063	0.065
Mean Y (NW)	0.070	0.068	0.069	0.072
Controls				
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	0.059	0.055	0.059	0.062
Mean Y (NW)	0.067	0.066	0.066	0.071
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	0.078	0.072	0.081	0.079
Mean Y (NW)	0.079	0.076	0.083	0.079
Controls				
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 highest education level of the female profile. 'Mean Y' shows the average value of the dependent variable across all female profiles whereas '**Mean Y (NW)**' shows the average value of the dependent variable for female profiles which are **not working**. Fixed effects reflect controls for female profile characteristics; male profile controls include 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 male (suitor) profile in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A.15: Effect of Female Work Status on Male Interest (by Education of Male Suitors)

	(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	0.062	0.067	0.059	0.068
Mean (NW)	0.070	0.093	0.065	0.067
Controls				
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	0.059	0.058	0.057	0.064
Mean Y (NW)	0.067	0.089	0.063	0.066
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	0.078	0.098	0.071	0.084
Mean Y (NW)	0.079	0.107	0.072	0.072
Controls				
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 currently employed and zero otherwise. Column (1) shows the overall effect while columns (2)-(4) show the effect by the education of the male profile. 'Mean Y' shows the average value of the dependent variable across all female profiles whereas **'Mean Y (NW)'** shows the average value of the dependent variable for female profiles which are **not working**. Fixed effects reflect controls for female profile characteristics; male profile controls include male profile's highest level of education (column 1), 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 male (suitor) profile in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A.16: Effect of Work Status on Male Interests: Conditional on Female Profile Viewership (by Caste of Male Suitors)

	(1)	(2)	(3)	(4)
	Overall	Brahmin	Other High Castes	Scheduled Castes
Panel A : Overall				
Working	0.000	−0.016**	0.003	0.022*
	(0.004)	(0.007)	(0.004)	(0.012)
Observations	108619	22802	76831	8986
Mean Y	0.189	0.190	0.191	0.171
Mean Y (NW)	0.196	0.213	0.195	0.159
City × Caste FE	✓	✓	✓	✓
Education FE	✓	✓	✓	✓
Male Profile controls	✓	✓	✓	✓
Panel B : Delhi				
Working	−0.000	−0.020**	0.002	0.028**
	(0.004)	(0.008)	(0.005)	(0.014)
Observations	81847	17711	57212	6924
Mean Y	0.190	0.198	0.190	0.176
Mean Y (NW)	0.198	0.226	0.194	0.160
Panel C : Bangalore				
Working	0.002	−0.001	0.002	0.009
	(0.007)	(0.015)	(0.008)	(0.025)
Observations	26772	5091	19619	2062
Mean Y	0.185	0.162	0.194	0.155
Mean Y (NW)	0.188	0.162	0.198	0.157
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 male profile. We keep only the female profiles which are shown to have been viewed by the male suitors by the platform. 'Mean Y' shows the average value of the dependent variable across all female profiles whereas '**Mean Y (NW)**' shows the average value of the dependent variable for female profiles which are **not working**. Fixed effects reflect controls for female profile characteristics; male profile controls include 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 male (suitor) profile in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A.17: Effect of Occupation Type on Male Interests (Conditional on Female Profile Viewership)

	(1)	(2)	(3)
	Overall	Delhi	Bangalore
Not working	−0.004	−0.003	−0.006
	(0.004)	(0.004)	(0.007)
Working - Neutral	−0.005**	−0.005*	−0.005
	(0.003)	(0.003)	(0.005)
Working - Masculine	−0.006**	−0.006**	−0.006
	(0.002)	(0.003)	(0.004)
Observations	108619	81847	26772
Mean Y	0.189	0.190	0.185
Mean Y (F)	0.192	0.193	0.188
Masculine=Neutral	[0.635]	[0.625]	[0.860]
Controls			
City FE	✓		
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. We keep only the female profiles which are shown to have been viewed by the male suitors by the platform. 'Mean Y' shows the average value of the dependent variable across all female profiles whereas '**Mean Y (F)**' shows the average value of the dependent variable for female profiles which are working in **'feminine'** occupations. Fixed effects reflect controls for female profile characteristics; male profile controls include 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 male (suitor) profile in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. *p*-values reported in square brackets.

Table A.18: Effect of Occupation Type on Male Interests: Conditional on Female Profile Viewership (by Caste of Male Suitors)

	(1)	(2)	(3)	(4)
	Overall Castes	Brahmin	Other High Castes	Scheduled
Panel A : Overall				
Not working	−0.004	0.012	−0.007	−0.017
	(0.004)	(0.008)	(0.004)	(0.013)
Working - Neutral	−0.005**	−0.002	−0.008**	0.008
	(0.003)	(0.006)	(0.003)	(0.008)
Working - Masculine	−0.006**	−0.011*	−0.006**	0.008
	(0.002)	(0.006)	(0.003)	(0.008)
Observations	108619	22802	76831	8986
Mean Y	0.189	0.190	0.191	0.171
Mean Y (F)	0.192	0.191	0.194	0.170
City × Caste FE	✓	✓	✓	✓
Education FE	✓	✓	✓	✓
Male Profile controls	✓	✓	✓	✓
Panel B : Delhi				
Not working	−0.003	0.017*	−0.008	−0.023
	(0.004)	(0.009)	(0.005)	(0.015)
Working - Neutral	−0.005*	0.001	−0.008**	0.007
	(0.003)	(0.006)	(0.004)	(0.009)
Working - Masculine	−0.006**	−0.010	−0.007**	0.009
	(0.003)	(0.006)	(0.004)	(0.010)
Observations	81847	17711	57212	6924
Mean Y	0.190	0.198	0.190	0.176
Mean Y (F)	0.193	0.196	0.194	0.175
Panel C : Bangalore				
Not working	−0.006	−0.009	−0.006	−0.003
	(0.007)	(0.016)	(0.009)	(0.025)
Working - Neutral	−0.005	−0.015	−0.005	0.013
	(0.005)	(0.013)	(0.006)	(0.015)
Working - Masculine	−0.006	−0.016	−0.004	0.006
	(0.004)	(0.011)	(0.005)	(0.013)
Observations	26772	5091	19619	2062
Mean Y	0.185	0.162	0.194	0.155
Mean Y (F)	0.188	0.174	0.196	0.151
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. We keep only the female profiles which are shown to have been viewed by the male suitors by the platform. 'Mean Y' shows the average value of the dependent variable across all female profiles whereas **'Mean Y (F)'** shows the average value of the dependent variable for female profiles which are working in **'feminine'** occupations. Fixed effects reflect controls for female profile characteristics; male profile controls include 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 male (suitor) profile in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A.19: Effect of Work Status on Male Interests (by Patriarchy Index and Share of Domestic Work)

	(1)	(2)	(3)	(4)
Z =	Patriarchy Index		DW Share	
	Levels	> Top Qt	Levels	> Top Qt
Working	−0.003	−0.004	−0.005**	−0.005***
	(0.003)	(0.003)	(0.002)	(0.002)
Z	−0.004	0.012***	−0.003	0.001
	(0.004)	(0.004)	(0.004)	(0.004)
Working × Z	−0.008**	−0.007*	−0.008***	−0.008***
	(0.003)	(0.004)	(0.003)	(0.003)
Observations	309267	309267	309267	309267
Mean Y	0.063	0.063	0.063	0.063
Mean Y (NW)	0.071	0.071	0.071	0.071
Controls				
City FE	✓	✓	✓	
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 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. The main explanatory variable is interacted with a Patriarchy Index constructed from NFHS 5 (columns 1-2) and Share of Domestic Work (DW) performed by women (columns 3-4). We include these variables in two forms - standardized levels (columns 1 and 3) and a dummy that takes a value of one when value of the underlying variable is above the topmost quartile and zero otherwise (columns 2 and 4). 'Mean Y' shows the average value of the dependent variable across all female profiles whereas '**Mean Y (NW)**' shows the average value of the dependent variable for female profiles which are **not working**. Fixed effects reflect controls for female profile characteristics; male profile controls include 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 male (suitor) profile in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A.20: Effect of Occupation Type on Male Interests (by Patriarchy Index and Share of Domestic Work)

	(1)	(2)	(3)	(4)
Z =	Patriarchy Index		DW Share	
	Levels	> Top Qt	Levels	> Top Qt
Not Working	0.004	0.005*	0.005**	0.006***
	(0.003)	(0.003)	(0.002)	(0.002)
Working - Neutral	0.002	0.003	0.002	0.002
	(0.002)	(0.002)	(0.001)	(0.001)
Working - Masculine	−0.000	0.001	−0.001	−0.001
	(0.002)	(0.002)	(0.001)	(0.001)
Z	−0.011***	0.008**	−0.010***	−0.005
	(0.003)	(0.003)	(0.003)	(0.003)
Not Working X Z	0.006*	0.004	0.006**	0.006*
	(0.004)	(0.004)	(0.003)	(0.003)
Working - Neutral X Z	−0.003	−0.004*	−0.004*	−0.004**
	(0.002)	(0.002)	(0.002)	(0.002)
Working - Masculine X Z	−0.002	−0.004*	−0.002	−0.003
	(0.002)	(0.002)	(0.002)	(0.002)
Observations	309267	309267	309267	309267
Mean Y	0.063	0.063	0.063	0.063
Mean Y (F)	0.063	0.063	0.063	0.063
Controls				
City FE	✓	✓	✓	
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 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 female profile who is not currently employed and zero otherwise; 'Masculine' takes a value of one if a female profile is engaged in a Masculine occupation and zero otherwise; 'Neutral' takes a value of one if a female profile is engaged in a gender neutral occupation and zero otherwise. The reference group for occupation type is females profiles engaged in feminine (F) occupations. Details on occupational classification based on gender distribution are discussed in section 3. The main explanatory variables are interacted with a Patriarchy Index constructed from NFHS 5 (columns 1-2) and Share of Domestic Work (DW) performed by women (columns 3-4). We include these variables in two forms - standardized levels (columns 1 and 3) and a dummy that takes a value of one when value of the underlying variable is in the topmost quartile and zero otherwise (columns 2 and 4). 'Mean Y' shows the average value of the dependent variable across all female profiles whereas '**Mean Y (F)**' shows the average value of the dependent variable for female profiles which are working in '**feminine**' occupations. Fixed effects reflect controls for female profile characteristics; male profile controls include 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 male (suitor) profile in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A.21: Effect of Female Work Status on Male Interest (by Other Characteristics of Male Suitors)

	(1)	(2)	(3)
	Overall	Delhi	Bangalore
Panel A: 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
Mean Y (NW)	0.067	0.065	0.075
Panel B: 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
Mean Y (NW)	0.070	0.068	0.075
Panel C: 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
Mean Y (NW)	0.118	0.120	0.108
Panel D: 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
Mean Y (NW)	0.062	0.060	0.071
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 set of male profiles that have at least as much education as the fictitious female profile, Panel B keeps the set of male profiles that have at least as much household income as the fictitious female profile, Panel C keeps set of male profiles to those that match the fictitious female profile on caste and Panel D keeps the male profiles that have lower age than a median male profile on the platform. 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. Fixed effects reflect controls for female profile characteristics; male profile controls include 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. 'Mean Y' shows the average value of the dependent variable across all female profiles whereas '**Mean Y (NW)**' shows the average value of the dependent variable for female profiles which are **not working**. Standard errors clustered at the level of the male (suitor) profile in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A.22: Effect of Female Work Status on Male Interest (by Manager of Male Suitors' 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)
Observations	94437	81018	13419	232407	182448	49959
Mean Y	0.058	0.056	0.071	0.064	0.060	0.079
Mean Y (NW)	0.062	0.062	0.061	0.073	0.070	0.084
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. Columns (1)-(3) are for a set of male profiles which are managed by family while columns (4)-(6) are for profiles managed by self. Fixed effects reflect controls for female profile characteristics; male profile controls include male profile's highest level of education, age, height, caste category, income and whether income is less than that of the corresponding fictitious female profile. 'Mean Y' shows the average value of the dependent variable across all female profiles whereas '**Mean Y (NW)**' shows the average value of the dependent variable for female profiles which are **not working**. Standard errors clustered at the level of the male (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 (TUS) data are from 138,799 households across all states of India conducted in 2019 by the National sample Survey Organisation of India. It is a cross-sectional data which is nationally representative. We keep only urban married women aged 20-45 in the households for the analyses.

The TUS adopted the interview 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 1 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 after marriage 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 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 across all profiles. We provided additional information for the following characteristics:

- **Full Name**: The full name of the user. It is not visible to the interacting men, but we assigned one anyway from a list of common names and last names for profile creation (based on the 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. 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-class".

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

- **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.