Beauty Premia in Wage Offers: Evidence from Vietnamese Online Job Postings*

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Abstract

We analyze a sample of nearly 40,000 gender-targeted online job vacancies in Vietnam from February 2019 to July 2020 to estimate wage offer premia for physical attractiveness and how they vary between genders. Specifically, we compare the monthly wages offered in matched vacancies with and without attractiveness requirements for job advertisements targeting men and women separately. Our findings indicate that physically attractive women are offered a wage premium of about five percentage points, whereas physically attractive men are not. Further analysis reveals that gender differences in the wage offer premia to physical attractiveness are mainly driven by attitudes toward gender roles and the perceived lack of fit rather than by the potential productivity-enhancing effects of physical attractiveness in certain occupations.

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Highlights

- Physically more attractive women are offered 5% higher salary than less attractive women in online job postings.
- No such premium is found for men.
- This "beauty premium" for women is mainly present in the Northern region, where more traditional attitudes toward gender roles persist.
- The largest premia are observed in job postings with the lowest experience requirements and lowest job positions.
- These premia are also present in occupations with minimal interpersonal interactions, where physical beauty is not a productivity-enhancing trait.

1 Introduction

Several studies have documented a relationship between physical appearance and earnings. One pivotal study by Hamermesh and Biddle (1994) established the groundwork for subsequent research. Using interviewers' ratings of respondents' physical appearance, it shows that physically less attractive individuals typically earn less than those with average looks, who, in turn, earn less than those considered good-looking. Better-looking individuals also have higher status in the workplace (Hamermesh, 2006) or a higher probability of employment (Babin et al., 2024). The effect of physical appearance on earnings has also been shown to vary between genders and occupations.[1]

Previous literature has predominantly focused on realized wages. In this study, we focus instead on the impact of physical attractiveness on posted wages, a dimension that has received comparatively less attention. Unlike wages, which reflect a market outcome, the relationship between posted wages and stated physical attractiveness preferences in job postings can be thought of as directly revealing how employers price physical attractiveness before adjusting wages for workers' idiosyncratic characteristics that may be observable to them but not to the analyst. Additionally, the information contained in job postings can enable us to account for important sources of variation, including the detailed roles involved and the specific skills required for each position. This type of information is often scarce for realized wages but is essential for arriving at unbiased estimates of wage disparities (Christl and Köppl-Turyna, 2020).

Our analysis relies on online job advertisements in the Vietnamese labor market. This is a powerful laboratory for exploring gender differentials in returns to physical attractiveness, for three reasons. First, while stating a preference for a specific gender or physical appearance is uncommon in most developed countries due to stricter legal frameworks, it remains common practice in many developing countries, including Vietnam. Second, online vacancy datasets often do not include remuneration data (e.g., Brenčič, 2012; Marinescu and Wolthoff, 2020), but including salary information is common on Vietnamese job boards. Finally, gender stereotypes and traditional family/social norms persist in Vietnam and still heavily influence economic decision-making. The regional disparity in gender norms and attitudes between the Northern and Southern regions provides an additional source of variation that allows us to investigate the mechanisms through which physical attractiveness is valued differently in female and male workers.

[1] Doorley and Sierminska (2015) find that the male beauty premium is present throughout the wage distribution, while the female beauty premium is concentrated at the bottom of the wage distribution. Other studies do not find attractiveness effects among men but rather a significant premium of about 2% for attractive females (Patacchini et al., 2014). Deryugina and Shurchkov (2015) find that the attractiveness premium in a particular job depends on the extent to which the job involves interaction with others.

The online job postings in our dataset are automatically collected from a leading job board in Vietnam over the period from February 2019 to July 2020. Nearly 40,000 gender-targeted job vacancies cover ninety-seven job designations in high- and low-skilled labor market segments. The postings include information on the required education level, experience level, job position, and place of work. There is a high occurrence of gender-biased job postings (nearly one-third) and a non-trivial occurrence of requests for physical attractiveness (10% of male-targeted and 29.2% of female-targeted ads). More than half of the postings (52.41%) also specify the level of monthly pay.

To estimate the pay offer premium associated with physical attractiveness, we first quantify the preferences for gender and attractiveness in each posting as revealed by the textual information in the posting, using a text-matching technique that employs a sentence-level text transformer. To ensure comparability, we pre-match all job postings by narrowly defined job titles so that each matched pair represents identical job roles. We then study how the advertised pay level varies with gender and attractiveness preferences within matched posting pairs that differ in their physical attractiveness requirements but are similar in other dimensions, making them equally likely to include physical attractiveness requirements based on their other characteristics.

When we abstract from job postings that do not include wage information, our estimates suggest beauty premia of 3.7–5.2 percentage points for women and a small but statistically significant negative premium for men. Moreover, the wage offer premium for physically attractive women is highest in job advertisements with minimal experience requirements, gradually diminishing as experience requirements increase and eventually turning into a penalty for positions requiring more than five years of experience.

However, if we simply excluded postings that omit salary information from the analysis (a significant fraction of our sample), we would neglect the selection bias that could potentially arise from differences in unobservable characteristics between job postings that contain salary information and those that do not. Specifically, as shown by Brenčič (2012), employers are systematically less likely to post a wage offer when trying to fill high-skill vacancies. To address this, we derive a second set of estimates using a Heckman-type two-step procedure. The first step involves estimating a Probit model to predict the probability of quoting a salary, generating estimates for the Inverse Mills Ratio (IMR). These IMR estimates are then incorporated into the second step matching procedure, alongside textual information, and are also included in the wage equations in the second stage.[2] When using this procedure, the beauty premium for women rises to 5.4 percentage points. Additionally, the negative premium for jobs with the highest

[2]To the best of our knowledge, our study is the first in this literature to use a Heckman two-step correction to improve the accuracy of estimates of premia for physical attractiveness.

experience requirements vanishes, suggesting a strong selection bias against including salary information in postings for jobs of this type.

We find no difference when we compare postings for positions that require interpersonal interactions—where physical appearance could be directly associated with higher productivity—with those for positions involving minimal interpersonal interactions. This finding indicates that the premium we estimate is unlikely to reflect a positive productivity-enhancing effect of physical attractiveness. We find no evidence for either the view that employers who engage in frequent and extensive job postings tend to use similar job descriptions for all positions or that the beauty premium can be attributed to noise or negligence by employers in job postings.

Our findings of a gender differential in the beauty premium align with the existing evidence (French, 2002; Babin et al., 2020). Possible explanations for this gender gap include differences in traditional gender roles (Anastasi, 1981). Indeed, focusing on historically determined regional disparities in attitudes towards gender roles, as proxied by sex ratio imbalances and cultural disparities between the Northern and Southern regions, we find evidence that traditional norms play some role.[3]

Our study builds on and contributes to three additional strands of literature. The first strand is the broad literature that uses online vacancies to identify sources of wage offer disparities. For example, using online job vacancies collected from a job board of the public employment administration in Austria, Ziegler (2020) finds that managerial and analytical skills have the largest explanatory power in pay. Using Mexican online job posting data, Arceo-Gomez et al. (2020) identify implicit gender stereotype content in the job ad text and show that the gender wage gap appears larger in implicitly gender-targeted ads than in explicit ones. Marinescu and Wolthoff (2020) use vacancy data from a leading US job board and document the role of words in the job title in explaining the variance in posted wages. Our contribution to this literature is examining a previously unexplored predictor of wage offers: gender roles and attitudes that shape employers' preferences for physically attractive female workers. Unlike prior research that primarily explores observable or measurable job skills and worker characteristics, our study focuses on a socio-cultural dimension.

The work closest to ours is Arceo-Gomez et al. (2022), which also examines the effect of physical appearance requirements on wage offers in gender-targeted vacancies. However, it should be noted that there are notable distinctions between the two studies.

[3]Another factor that might contribute to this gender differential is that men are more likely to hold high positions in the workplace and so any gender-neutral preference for physically attractive subordinates of the opposite sex translates into a stronger beauty premium for women on average (Haveman and Beresford, 2012).

First, using vacancies from three different Mexican job search websites, Arceo-Gomez et al. (2020) find beauty premia in both female-targeted and male-targeted advertisements across all three platforms. However, the findings regarding whether beauty premia are greater for women compared to men show inconsistent results. In contrast, we focus on the differences in beauty premia between genders and show that good looks have stronger wage implications for women than for men. Second, we provide evidence that gender role attitudes serve as the channel through which physical attractiveness plays a more crucial role in women-biased vacancies than in men-biased ones.

Also relevant to our work is the long-standing strand of literature on the consequences of gender role norms on women's labor market outcomes, such as labor supply, employment, earnings, and career advancement opportunities. These studies have primarily focused on traditional gender roles, placing household and family responsibilities largely on women, which in turn limits their participation in the labor market. As a result, women tend to work shorter or more irregular hours compared to men, take career breaks more frequently, and sort into different occupations and industries (e.g., Eagly and Karau, 2002; Alesina et al., 2013; Bertrand, 2018). For example, Cavapozzi et al. (2021) study the impact of peers' attitudes toward gender roles on the labor supply of UK mothers and find that mothers who have peers with gender-egalitarian norms are more likely to have a paid job and contribute a larger share of the total paid hours worked within their household. We complement these contributions by examining the impact of gender role attitudes on the wages offered to women depending on their physical attractiveness.

Finally, this paper is related to the growing economic literature that applies semantic similarity algorithms for causal inference. For instance, Ehrmann and Talmi (2020) analyze central banks' press release data and find that higher text similarity among subsequent press releases is associated with lower financial market volatility. Employing data on public comments on U.S. federal regulatory rulemaking, Bertrand et al. (2021) provide evidence that foundations' charitable grants reach targeted nonprofits just before those nonprofits engage in public commentary. The comments made by firms and non-profits appear to have some systematic similarity in their content. Existing studies use different algorithms to convert words or documents into vector representations, such as the bag-of-words model (representing a document as a count vector of its constituent words) or word embedding models (e.g., GloVe and Word2Vec, which produce embeddings that are similar for words appearing in similar corpus contexts). Yet, a limitation of these methods is their context independence, whereby they assign only a fixed vector to a word regardless of its position in a sentence and the different meanings it might have. We make a methodological contribution to this literature by utilizing

BERT, the state-of-the-art sequence embedding model. This model allows the meaning of a word to depend on its neighboring words, thus better capturing subtle nuances in meaning and producing more accurate representations of words within their contexts.

The remainder of the paper is structured as follows: Section 2 describes the institutional background and the dataset employed in our analysis, Section 3 outlines our empirical strategy, Section 4 presents our findings, Section 5 concludes.

2 Data

2.1 Institutional background

The Vietnamese labor market is one of the largest in Southeast Asia, comprising approximately 56 million people. Despite the nation's rapid economic growth, the economic empowerment of women remains a challenge. The gender gap in labor force participation has been stable, with females having a consistently lower participation rate than males (World Bank). In 2020, the labor force participation rate was 75% among females and 84% among males.[4]

Compared to other countries at a similar stage of development, Vietnam also has a markedly high Sex Ratio at Birth (SRB, i.e., the ratio of male to female births), with significant variation across regions. In 2018, among the six regions, the highest estimated SRBs are observed in the Northern areas (Chao et al., 2021), specifically the Red River Delta (1.141) and the Northern Midlands and Mountain areas (1.131). The Southern regions, including the Mekong River Delta (1.072) and the Central Highlands (1.068), have the lowest estimated SRBs. The remaining two regions, the Southeast and the Northern Central/Central Coastal Areas have ratios of 1.122 and 1.116, respectively.

Income and salary levels in Vietnam exhibit considerable gender-based disparities. In 2019, the average monthly income for salaried workers amounted to VND 7 million, with males earning 1.2 times more than their female counterparts. This is partly attributed to the fact that, despite representing roughly 45% of the labor force, working women in Vietnam are underrepresented in the top positions. Additionally, a significant gender gap exists in educational attainment, with males averaging 7.52 years of education compared to 6.94 years among females, according to the 2010 Vietnamese Household Survey (Duong, 2015).

Gender-based discrimination in the workplace is explicitly prohibited in Vietnamese law. Vietnam's 2012 Labor Code, for instance, safeguards "female employees' right to

[4]Source: `https://data.worldbank.org/indicator/SL.TLF.ACTI.MA.ZS?locations=VN`, accessible 10th November 2024.

work on an equality basis" and requires employers to "ensure the implementation of gender equality and measures to promote gender equality in recruitment, employment, training, working hours, and rest periods, wages, and other policies". The Law on Gender Equality further emphasizes equal treatment for men and women in various aspects of employment, including recruitment, wages, pay and bonuses, social insurance, working conditions, training, and promotion. Additionally, according to the 2012 Labor Code (Prohibited Act 1, Article 8), employers are prohibited from performing discrimination at work based on workers' disabilities, gender, marital status, race, or skin color.

While these laws and policies establish a robust legal framework to prevent gender-based discrimination, their practical implementation remains a challenge. For instance, despite legal provisions in the 2012 Labor Code explicitly stating that maternity leave should be considered part of an employee's length of service, the survey evidence shows that a substantial 40 percent of Vietnamese employers do not comply with this requirement (ILO, 2015).

2.2 Data collection and processing

Our dataset contains publicly available job vacancies collected from one of the most widely accessed Vietnamese online job boards over the seventeen-month period from February 2019 to July 2020. Online vacancy data has been shown to offer several advantages for labor market research. Compared to traditional methods such as employer, employee and household surveys, collecting web-based data has the advantage of being time- and cost-effective (Steinmetz et al., 2014). Additionally, thanks to both the nature of the data (i.e., granular and high frequency) and the use of new textual analytic methods (e.g., Natural Language Processing), the content of online job posts can provide new and more detailed information than that provided by traditional data sources (Kureková et al., 2015).

To construct our dataset, we wrote a Python script to automatically scrape vacancies from the job portal every week. A typical job vacancy contains detailed information, including job title, category, job level, job type, work location, job description, preferred gender, education level, experience level, job requirements, offered monthly salary, firm's name, and number of employees. Since we cannot track whether a vacancy is filled, we rely on the ID number assigned to each job posting to identify unique vacancies and eliminate duplicates.

Our full sample consists of 259,633 full-time job postings. Of these, 137,142 quote a salary (at a level either matching or above the statutory minimum wage), while 122,491 do not include salary information. As shown in Table 1—and consistent with the findings of Brenčič (2012) and Banfi and Villena-Roldan (2019)—postings that do not quote a salary tend to have higher skill requirements compared to those with salary information. For instance, positions with salary information often require only a high school education, while those without salary information more frequently demand a university degree and are often managerial positions. The proportion of job postings with and without salary information also varies across locations, with job postings containing salary information being more prevalent in the two largest cities, Ha Noi and Ho Chi Minh City, and those without salary information being more common in smaller cities.

[Table 1 here]

Table 2 reports the proportions of job postings that mention physical attractiveness preferences for the two sub-samples (with and without salary information). Job postings without salary information are less likely to mention physical attractiveness preferences, and a smaller proportion of them are gender-targeted—in line with the findings of Kuhn and Shen (2013). For instance, among positions requiring a high school education, 31.9% of job postings with salary information mention looks, while only 19.2% of those without salary information do so. This pattern holds across vocational training, associate degree, university degree, and other education categories. However, as skill requirements increase, the likelihood of specifying physical attractiveness preferences tends to decrease, independently of whether salary information is provided.

In terms of job position, for both new entry/internship and non-managerial jobs we see attractiveness requirements mentioned more frequently in postings with salary information than in corresponding postings without salary information. Similarly, across experience levels and locations, attractiveness requirements are consistently mentioned more often in postings that include salary information, is in line with previous literature findings (Kuhn and Shen, 2013; Chaturvedi et al., 2024).

[Table 2 here]

As the focus of our paper is on the wage offer returns to physical appearance, our estimates are mostly based on the subsample of job postings with salary information. However, in some specifications, we incorporate a first-stage selection stage based on the full sample.

In the subsample of vacancies explicitly quoting salary, 12.3% of the job posts mention physical attractiveness as a requirement. Besides physical appearance, 28.4% of all postings mention an explicit requirement for a specific gender. Among these gender-targeted ads, nearly two-thirds of job ads report a preference for male candidates. Since our analysis focuses on gender differentials in beauty premia, we restrict our sample to vacancies that state a preference for a specific gender (i.e., male- or female-targeted ads). In total, we have a sample of 38,945 unique gender-targeted job ads including salary information, with attractiveness preferences present in 10% of men-targeted and 29.2% of women-targeted ads.

Overall, as shown in Appendix Table A3, gender-specified job ads are more likely to require a lower level of education and are less likely to target university graduates compared to job postings that do not specify gender. These gender-specific job postings also tend to be for new entry and non-managerial positions, with fewer targeting managerial roles. Similarly, job postings that ask for good looks are less likely to require a high level of education, require less work experience, and are often for new entry and non-managerial positions compared to job ads that do not specify physical attractiveness.

We put the data through a few reconciliation and cleaning steps. We first convert the salary amounts quoted in US dollars to Vietnamese dong using the daily exchange rate when the job ad is first posted. For job ads quoting a range of salaries, we calculate the average wage.[5] Additionally, we restrict our analysis to postings that offer a salary at least as much as the obligatory minimum wage.[6]

We perform further processing steps at the vacancy level. The job title itself can explain a large proportion of the variation in posted salaries and reflect the level of education, experience, and specialization of different jobs. Hence, for each posting, we use the text referring to the job type to classify vacancies into 97 different narrowly defined job titles.[7] We also process any text that refers to the industry where the vacancy is to classify vacancies into 43 separate industries and categorize the size of recruiting firms based on the number of their employees. As shown in Figure A1, most job ads are posted by medium-sized companies with 100 to 499 employees.

We also use *pyvi*, a natural language processing Python package, to extract a set of all unique keywords referring to the required skills from the unstructured text of job requirements. From this set of keywords, those that indicate skills are selected and categorized into twelve different skill groups. Our first ten skill groups are defined according to Deming and Kahn (2018), including cognitive, social, character, writing, customer service, project management, people management, financial, computer (general), and

[5]Results for baseline regressions (reported in Appendix Table A7 and A8) remain robust when we choose the minimum and maximum wage levels instead.

[6]The minimum wage is set at VND 2,920,000 according to the Decree number 157/2018/ND-CP (effective since the 1st of January 2019).

[7]The full list of job titles is reported in Appendix Table A1.

software (specific). To better reflect the skill demands in the Vietnamese labor market, two additional skill groups have been incorporated: foreign language skills and artistic skills. We consider a vacancy as requiring a particular skill group if it contains one or more keywords or phrases listed in that group. The list of specific examples of keywords for each skill category is found in Appendix Table A2. This text-scanning approach is also applied to obtain information on preferences for physical appearance. We categorize a job posting as indicating a preference for physical attractiveness if it includes one or more keywords indicating physical attractiveness in Vietnamese, such as "pretty face," "(physically) attractive," "good-looking," etc.[8]

For each posting, we also extract information on the vacancy's geographical location (city and province) from the text of the job ad. As can be seen from Figure A2, most advertised jobs are located in Ha Noi and Ho Chi Minh City (HCM). This is not surprising, given that those cities are the two major cities in Vietnam in terms of politics and economics. Other locations with high shares of vacancies, such as Da Nang, Hai Phong, Binh Duong, and Bac Ninh, are industrialized or port cities. For simplicity, we classify vacancies into three location categories: Ha Noi, HCM, and other cities.

While online vacancy data shows great promise for labor economics research, there are several limitations that should be acknowledged. First, online job postings do not cover all sectors and industries of the labor market, nor do they include public sector jobs (Pham et al., 2023). Second, job postings for more highly educated workers are overrepresented (Carnevale et al., 2014). Indeed, most job postings in our data require candidates with a degree or specialized training (95.5% of the sample), compared to an estimated 27% of workers who had a degree or training certificate in 2023.[9]

2.3 Gender-targeted job postings

We can pick up some patterns from the bivariate correlations for each pair of job characteristics and skill requirements reported in Appendix Table A4. First, cognitive, writing, people management, and project management skills are positively correlated with each other, with education and years of experience, and with most of the other nine job skills.

[8]We use a comprehensive list of synonyms for the term "beauty" or "attractive" sourced from the Vietnamese dictionary. Height and age are only two dimensions of physical appearance and do not adequately capture the complexities of physical attractiveness (Mavisakalyan, 2018). Hence, we do not include height and age-related terms in our selection of beauty keywords. Instead, we report results from models that control for height and age requirements in Online Appendix Table A6 and find that results for the beauty effects remain consistent with those from our main models.

[9]Source: `https://www.vietnam-briefing.com/news/vietnams-labor-market-moving-into-2024.html/`, accessible 10th November 2024.

This finding implies that they are general skills that are viewed as essential by employers across a wide range of occupations and industries. Second, the correlations between attractiveness preference and the requirements for education, experience, and job position are mostly negative, suggesting that physical attractiveness preferences are more likely to feature in postings for low-skilled jobs.

Table 3 provides summary statistics of required education, experience, and job level variables for subsamples of female- and male-targeted vacancies. On average, postings preferring women offer 12.7% lower salaries (i.e., VND 7,752,873) than postings preferring men (i.e., VND 8,882,292). Many gender-targeted vacancies target educated and early-career candidates with little to no work experience. Notably, only a marginal proportion of job vacancies for men (i.e., 0.6%) and for women (i.e., 0.2%) do not mention a specific education level. Among those that specify education levels in both men and women subsamples, nearly one-third of the job ads require an associate degree, and one-fifth require a bachelor's degree. Further, around 40% of job postings ask for less than one year of experience. The number of gender-targeted vacancies decreases as the required years of experience increase. Regarding job level, the majority of our postings (i.e., 84.7% and 88.7% for male and female-targeted postings, respectively) seek candidates for non-managerial/employee positions, and only a limited number of jobs are advertised for new entry and managerial positions.

[Table 3 here]

Table 4 provides summary statistics of job location and required skill variables for subsamples of female- and male-targeted vacancies. A significant share of gender- targeted job postings is concentrated in the two largest cities. In terms of requested skills, many postings prioritize character and social skills. In contrast, more specialized skills, such as financial expertise, people management, artistic abilities, and writing skills, are among the least frequently mentioned.

[Table 4 here]

According to Table 5, stating preferences for good looks is more likely in jobs requiring a lower level of education and experience and those in non-managerial positions. For example, among men-targeted ads, nearly 20% of those looking for intern/entry-level employees require good looks, while only 4% of those looking for managers mention such a requirement. Similarly, among women-targeted ads, nearly one-third of those looking for non-managerial positions targeting physically attractive candidates, whereas 13.4% of those looking for managers include such a preference.

Ads for jobs in the two biggest cities ask for good looks as often as those in smaller towns. Interestingly, the statistics reported in Table 5 also reflect the gender differential in employers' preferences for physical attractiveness. Overall, the share of job postings asking for good-looking candidates among female-targeted ads is much higher than among male-targeted ads across all job types. For example, among job ads requiring one to two years of experience, the presence of physical attractiveness requirements in job postings targeting women is nearly ten times that in job postings targeting men (i.e., 35.5% vs. 3.7%).

[Table 5 here]

Further, the statistics on the frequency of requiring good looks by job industries, plotted in Appendix Figure A3, reveal that physical appearance plays a more important role for women than for men in most job sectors. Specifically, the frequency of stating physical appearance requirements in women-targeted postings is much higher than in men-targeted postings in the majority of industries, except for the IT sector, where the frequency of requiring good looks is substantially higher for men.[10] This finding is consistent with Kuhn and Shen (2013), Ningrum et al. (2020), and Chaturvedi et al.(2024), who document that employers are more likely to require good looks in female-targeted job ads compared to male-targeted job ads.

To investigate which specific job requirements and characteristics of vacancies are correlated with physical appearance preferences, we use the following Probit model:

$$\begin{aligned}\Pr\left(\mathit{Attractiveness}_{it} = 1 \mid X\right) \;=\; \Phi\big(&\beta_0 + \mathit{Skill}_{it}\beta_1 + <\mathit{Controls}>_{it}\beta_2' + \mathit{Quarter}_t + \mathit{Industry}_{s(i)} \\ &+ \mathit{Occupation}_{o(i)} + \mathit{Firm\_size}_{f(i)} + \varepsilon_{it}\big), \qquad (1)\end{aligned}$$

where i and t refer to the job posting and posted time (quarter), $s(i)$ is the industry that the firm posting the ad belongs to, $o(i)$ the occupation the posting is for, and cumulative standard normal distribution function, i.e., standard normal distribution N (0,1). *Attractiveness* is an indicator variable that equals one if the employer states a preference for physically attractive candidates and zero otherwise. *Skill* is a vector of twelve skill indicator variables (i.e., cognitive, social, character, writing, customer service, project management, people management, financial, computer, software, language and artistic), each of which indicates whether a certain skill appears in the job requirement. Moreover, we include in the model a set of control variables, including indicators for experience

[10]It is noteworthy that the IT job category is mostly made up by customer IT support technician occupation, which is mainly men-targeted and often requires good-looking since it involves substantial direct customer interactions.

level, education level, work location and job level. We also include quarter, job title, industry, and firm size controls. Detailed definitions of our variables are reported in Appendix Table A4.

Estimation results from (1), reported in Table 6, suggest that jobs requiring higher education levels are less likely to ask for good-looking candidates. For instance, among female-targeted ads, a posting requiring an associate degree or university degree is respectively 5.7% and 5.2% less likely to ask for good looks compared to a posting requiring a high school degree. Similar findings are evident among male-targeted ads, where the probability of stating a preference for good looks decreases by 4.7% to 5.0% when an education level higher than high school is required.

[Table 6 here]

Turning to the level of experience, we observe that job postings targeting highly experienced candidates are less likely to state preferences about physical attractiveness, especially among men-targeted postings. Specifically, among men-targeted postings, compared to postings requiring zero to less than one year of work experience, those requiring 1–2 years of experience exhibit a 2.6% lower likelihood of targeting attractive candidates. This pattern is less clear for women-targeted postings. In fact, the chance of a vacancy mentioning physical attractiveness increases by 4.5% and 3.3% when the required experience is 1–2 years and 2–5 years, respectively, compared to postings targeting early career candidates with less than one year of experience. When the required work experience exceeds five years, the likelihood of stating preferences for physical attractiveness appears to be lower, although the estimated coefficient is not statistically significant.

With regard to job positions, vacancies at the managerial level are less likely to seek good candidates, especially among female-targeted advertisements. Specifically, compared to entry-level jobs, the preference for attractive candidates in vacancies for managerial roles is 14% lower among female-targeted postings. Among men-targeted ads, the probability of asking for physical attractiveness is similar across job positions.

With regard to work location, interestingly, amongst postings targeting women, those for jobs located in the capital city Ha Noi have a 1.4% lower likelihood of targeting physically attractive job seekers. In contrast, among men's ads, those located in Ha Noi have a 2. 6% higher likelihood of preferring physically attractive candidates.

Physical appearance requirements are comparatively more likely in postings asking for managerial skills (i.e., project and people management) and soft skills (e.g., artistic, character, and social skills). In contrast, vacancies requiring hard skills such as software, cognitive, and foreign language skills are associated with a reduced preference for physically attractive candidates. This finding might indicate a sorting of preferences for physical attractiveness, which appears more often for tasks/occupations involving more interpersonal interactions among women-targeted postings. For male-biased ads, postings for job requiring hard skills (e.g., financial and cognitive skills) and soft skills (e.g., character and social skills) are more likely to include preferences for physical attractiveness than those requiring basic computer, project management, language, customer service, and writing skills.

3 Estimating the effects of physical appearance on posted wages

3.1 Matching

Our summary statistics suggest that job advertisements that include preferences relating to physical appearance have different characteristics and skill requirements from those that do not. Hence, we employ the matching technique to make our job vacancy sample more homogeneous. The matching approach aims to balance the unobservable job characteristics by adjusting for differences in observable characteristics among occupations. The main matching technique used in this study is text matching to investigate the return to physical attractiveness. The principle of this technique is pairing a non-beauty-biased job posting with the most similar job description (i.e., the whole text of a job vacancy) to a beauty-biased job posting. First, we convert all the text to lowercase and remove special characters and punctuation. Second, we pre-match job postings based on narrowly defined job titles, ensuring that each matched pair represents similar job roles for more accurate estimations.

Next, we transform the job vacancy texts into word embeddings. To perform this transformation task, we use Bidirectional Encoder Representations from Transformers (BERT), a transformer-based, pre-trained language deep-learning model widely adopted in recent years for various NLP tasks. Fundamentally, BERT converts a word or a sequence of text into an output vector sequence based on the context of the word. The specific model we use is a Sentence BERT (SBERT) model for Vietnamese sentence embeddings (Phan et al., 2022). This model relies on PhoBERT as the main transformer for word embeddings, which is pre-trained on a 1GB Vietnamese Wikipedia corpus and 50GB of Vietnamese news articles. Finally, vacancy (sentence) embeddings are computed by averaging embeddings of all words in that vacancy. After this transformation, a job posting is represented by a 512-dimensional vector.

The next step is to reduce embeddings' dimensionality. Previous research suggests that increasing word representations' dimensionality beyond 300 has negligible improvements for text analogy tasks such as text similarity (Pennington et al., 2014). Hence, we choose a standard dimension of 100 for small text corpora like job postings. A 100-dimensional embedding can be seen as a middle ground between too few dimensions, which would lose important variations in text meaning, and too many dimensions, which tend to increase noise. To do this, we use Uniform Manifold Approximation and Projection (UMAP), a dimensionality reduction technique. As a result, a job posting is represented by a 100-dimensional vector.

These embeddings, excluding those that refer to physical appearance requirements, are employed to calculate a text similarity score—a cosine similarity metric normalized between zero and one—between any postings that mention physical appearance preferences and those that do not. Then, based on this metric, matched pairs are obtained using neighbor matching with replacement (Abadie et al., 2006). To ensure that our postings are sufficiently similar within matched pairs, we drop from our sample the 10% of all matched pairs with the lowest similarity score. This process results in text-matched samples of 7,808 female-targeted ads and 4,482 male-targeted ads.

As a robustness check for the quality of our text matching process, we examine the differences in readability scores of job ad texts between postings with and without preferences for good looks before and after matching. The results presented in Online Appendix Table A8 indicate that prior to matching, there are significant differences in readability levels among postings with and without physical appearance preferences. However, post-matching, the readability levels among postings with and without physical appearance requirements show no statistically significant differences, suggesting that our matched job postings are comparable in content.

As a final step, we run the wage equation on text-matched samples to further control for any remaining covariate imbalances after matching using the following fixed-effects model:

$$LogWage_{it} = \beta_0 + \beta_1 Attractiveness_{it} + <Controls>_{it}\beta_2' + <Fixed\ Effects>_{it} + \varepsilon_{it}, \quad (2)$$

where i and t refer to job ad and time. LogWage$_{it}$ is the logarithm of offered salary for job posting i posted on date t. *Attractiveness* is an indicator variable that equals one if the employer prefers physically attractive candidates and zero otherwise. *Controls* is a vector of covariates, including job characteristics that are likely to affect wage (i.e., twelve skill groups, education and experience level, job position, location, and industry). *Fixed Effects* include time (i.e., the quarter when the job ad was first posted), job title and firm size fixed effects. ε_{it} is an error term.

To validate the results from our text matching approach, we also derive estimates using coarsened exact matching (CEM; Iacus et al., 2012) of appearance-biased ads with non-appearance biased ads based on a set of job characteristics (in conjunction with our two-step procedure). These matching characteristics are narrowly defined job title, required education, experience, job position, posted quarter and firm size. Since all matching covariates are categorical variables, our CEM algorithm is equivalent to the exact matching approach since it matches a treated unit to control units with the same matching characteristics values. For our CEM algorithm, exact one-to-one matching is performed. As a result, we obtain subsamples of 3,050 women-targeted and 1,370 men-targeted job vacancies after matching. Finally, we re-run model (2) on these CEM-matched samples to estimate the beauty premium on earnings for women and men, separately.

3.2 Selection into stating salary information

Selection bias arises if the unobservable characteristics of salary-posting job ads and hidden-salary job ads are systematically different from each other. Addressing this concern, we use the Heckman two-step procedure to correct for selection bias. The first step of this procedure involves estimating a Probit model for quoting salary information. In the second step, estimates of the Inverse Mills Ratio (IMR) obtained from the first step are incorporated in the matching procedure, as well as being included in the wage equation.

The Probit specification used in the first stage is as follows:

$$\begin{aligned} HaveSalary_{it} &= \alpha + \beta_1\, EmbeddingDimension_{1it} + \beta_2\, EmbeddingDimension_{2it} + \dots \\ &+ \beta_{10}\, EmbeddingDimension_{10it} + \beta_{11}\, Education_{it} + \beta_{12}\, Experience_{it} + \beta_{13}\, Position_{it} + \varepsilon_{it}, \quad (3) \end{aligned}$$

where: the embedding dimensions 1 to 10 are obtained from the 10-dimensional embedding of a job posting. We generate this 10-dimensional embedding using the Vietnamese S-BERT model described in the previous section. Subsequently, we use UMAP to reduce the high dimensionality to only ten dimensions. We further control for education, experience level, and job position. ε_{it} is an error term.

Model (3) is estimated for two separate subsamples of female-targeted and male-targeted postings. The estimated parameters are then used to calculate the IMR, which is incorporated into the second-step matching procedure. For text matching, the job ad text is first converted into a 512-dimensional vector using the SBERT model. This vector is then reduced to 100 dimensions using UMAP. The reduced embeddings and the IMR are subsequently standardized, and similarity scores between job ads are calculated using the Cosine index on these 101-element vectors. For CEM, the IMR is included in the matching equation along with other covariates, such as narrowly defined job titles, required education, experience, job position, posted quarter, and firm size.

Finally, we estimate wage regressions on the matched samples, controlling for all job ad characteristics as well as the estimated IMR. For the unmatched samples, the IMR is directly incorporated into the final wage regression.

4 Empirical findings

4.1 Effects of physical appearance on wage offers

Column (2) of Table 7 reports estimates of the beauty premium in wage offers for female workers from text-matched samples, focusing on the subsample of postings that include salary information. We find that physically attractive women are offered 3.7% higher salaries in postings targeting female candidates. In contrast, according to results in column (5), there is no significant beauty premium in postings targeting male candidates. Using CEM, we find a positive wage offer effect of 4.3% for physically attractive female candidates and no statistically significant wage offer effect for their male counterparts.

[Table 7 here]

While the existence of a beauty premium has been extensively documented in previous studies, there remains a lack of consensus on why it exists. Amongst the leading explanations for the beauty premium, some focus on the employee side of the relationship. One mechanism is self-selection of good-looking into high-paying occupations (Deryugina and Shurchkov, 2015). Another is that physical attractiveness may be positively correlated with health and cognitive abilities (Kanazawa, 2011), as well as communicative confidence and interpersonal skills (Mobius and Rosenblat, 2006).

Other explanations focus on employers. Employers may tend to overestimate the skills and abilities of good-looking workers once they meet them. In contrast, the discrimination hypothesis argues that the bias is due to employers' intrinsic preferences for hiring physically attractive people (Rooth, 2009). Our estimation results show that a beauty premium is already in evidence at the offer stage of the recruitment process. This is consistent with employers' having preferences for good looks ex ante, rather than good looks inducing biased beliefs about ability.

Our estimation results also show that women benefit more from being physically attractive than do men. This finding is generally consistent with prior literature (e.g., French, 2002; Abueg et al., 2020; Babin et al., 2020). One possible explanation for the gender differential in the beauty premium is rooted in the different traditional social roles defined for women and men. In particular, while women have traditionally been identified with the roles of wife, housekeeper, and child-bearer, their male counterparts have been expected to provide economic support for their families (Anastasi, 1981).[11] Indeed, Neilson and Ying (2016) show that hiring managers' taste for ascriptive characteristics, such as physical attractiveness, differs by gender: managers care more about beauty for women than for men. Another possible explanation points to gender differences in workplace hierarchies. Haveman and Beresford (2012) observe that men are more likely to hold high positions in the workplace (i.e., manager, supervisor, director) and thus to make decisions about salaries. In addition, men often discriminate in favor of physically attractive women, but not vice versa, and there is little effect of physical appearance on the ratings of men's performance (Kaplan, 1978; Guéguen, 2012). Thus, attractive women might be offered higher wages by their male employers, leading to a larger attractiveness premium among women.

The findings from the Heckman two-stage procedure are shown in Table 8. The coefficients on the inverse Mills ratio are negative and statistically significant, suggesting a significant selection bias (a negative correlation between a posting's salary offer and the likelihood of it mentioning salary information) and implying that estimates from a two-stage specification that adjusts for this bias should be more reliable. Estimates are qualitatively aligned with the baseline results across samples, both with and without matching. Even after accounting for selection bias in estimating the wage returns to attractiveness, we observe a significant beauty premium in wage offers for women and no corresponding premium for men. In quantitative terms, the premium for women rises from 3.7 to 5.4 percentage points when using matching. Results using CEM matching are in line with those obtained with our text matching technique: we find a statistically significant 2.7% attractiveness premium for women but no premium for men.

[Table 8 here]

[11] Bar-Tal and Saxe (1976) argue that physical attractiveness attracts a premium for women in the workplace because it is valued in relation to their traditional social roles. Despite dramatic changes in women's socioeconomic standing, studies show that the women's beauty ideal is still pervasive and continues to occupy a central role in their lives (Baker-Sperry and Grauerholz, 2003). Moreover, Jeffreys (2014) argues that women's growing social and economic status has been accompanied by increasing beauty-enhancing practices (i.e., makeup, diet, plastic surgery). As a result, physical beauty remains an advantageous trait for women in the labor market. While physical beauty is a highly desirable quality for women, it is considered less important for men and their traditional roles. In contrast to femininity, masculinity is comparatively more associated with other characteristics such as strength, power, and success. Physical attractiveness is not masculine; hence, it might not be rewarded in men.

To measure the specific effects of different traits on pay offers, we also construct separate component indicators for general attractiveness and more narrowly focused features—"pretty face" and "height". Figure 1 presents the results of this breakdown. For women, we find wage offer premia for general good looks, facial attractiveness, and height. No premia are found for men for any of these traits.

[Figure 1 here]

4.2 Heterogeneity across job types

Panels A and B of Figure 2 show estimates of attractiveness effects on pay offers at different job levels for women and men, respectively, when we do not control for selection bias related to the inclusion of salary information. The beauty premium in wage offers for women is highest, at 15.6%, in the lowest positions, progressively becoming weaker and eventually vanishing in upper-tier positions. For male-targeted postings, we see no beauty premium across job positions.

When controlling for selection bias using the Heckman two-step procedure, the find similar results. The beauty premium for women remains highest, at 13.9%, among the lowest positions, gradually weakening and vanishing in upper-tier positions. For men, there is still no beauty premium across job positions, except for a penalty of 18.4% at the lowest positions.

[Figure 2 here]

With regard to differences in experience levels, estimation results in Panels C and D of Figure 2 reveal that physically attractive women enjoy a pay offer premium of 6.5–8.1% in vacancies requiring less than one year of experience. This premium gradually declines for vacancies requiring more years of experience and even turns into a penalty of 27% for vacancies requiring more than five years of experience. A different pattern is observed among male-targeted ads. Specifically, men seem to be penalized for their attractiveness with 2.8–4.6% lower wage offers in vacancies requiring less than one year of work experience. Yet, when more years of experience are required, there is no significant beauty effect on pay offers for attractive men. Overall, our results reveal that the beauty effect for women is larger among lower work experience and job position categories.

A possible explanation for this finding is that, as shown by prior research (Quereshi and Kay, 1986; Zuckerman, 1993; Anýžová and Matějů, 2018), the return to physical attractiveness decreases with age; and experience is positively correlated with age.

Anýžová and Matějů (2018) use data from the Czech PIAAC Survey of Adult Skills to investigate the income advantages associated with attractiveness among employed women and men across three age groups: 16-30 years, 30–50 years, and 50–66 years. Their findings reveal that while there is no significant beauty premium for the youngest age group, a beauty premium is evident for women in their prime years (aged 30 to 50), whereas older women (aged 50 to 66) experience a beauty penalty.

However, the reversal we find for high-experience jobs for women and low-experience jobs for men (a negative beauty premium) poses a puzzle. If firms do not genuinely value physical attractiveness, they should not specify it as a requirement in upper-tier job postings—because it could restrict the labor pool, thereby increasing recruitment costs. Requiring good looks and then penalizing candidates for it appears contradictory. A possible explanation for these findings is that in market segments that value ability more than looks, attractiveness requirements may act as a signal that serves to reduce matching frictions. Specifically, by including attractiveness preferences, employers that place a comparatively lower weight on ability than on looks can attract good-looking, lower-ability applicants who are more likely to accept. On the other hand, by *not* including attractiveness preferences in the postings, employers that prioritize ability (but still might value physical attractiveness) can discourage applications from physically attractive, low-ability applicants.[12]

When we use the two-step procedure to control for selection bias in the inclusion of salary information, the negative premium for inexperienced males is still present, but that for experienced females vanishes (the estimated coefficient becomes positive, albeit statistically insignificant). This suggests that, for job postings targeting experienced women, compared with similar postings that include both attractiveness requirements and salary information, those that include only salary information are for higher-paying jobs—and thus systematically less likely to include any salary information at all. Incorporating the IMR in the matching process and including it as a control restores comparability.[13]

For other job characteristics, the magnitude and sign of their estimated coefficients reported in Tables 7 and 8 are comparable to those found in previous literature on wage determination, including Autor and Handel (2013) and Deming and Kahn (2018). In

[12] In observational terms, this is in line with the "beauty is beastly" effect discussed by Heilman and Saruwatari (1979) and Braun et al. (2015), whereby attractiveness benefits women in non-managerial positions but disadvantages women in managerial positions. The role of signals in job postings is discussed in Kuhn et al. (2020).

[13] This is not inconsistent with the idea that attractiveness requirement may signal lower-paying jobs with low-ability requirements, as discussed above.

particular, the positive coefficients (although statistically insignificant for some) for education categories imply higher wage offers for higher levels of education. Similarly, categories requiring more experience are associated with higher wage offer premia. In the same vein, postings for managerial positions are more likely to offer higher wages than those for non-managerial positions. The results remain similar when using the Heckman two-stage procedure.

Results for different skill groups are mixed. Specifically, the strongest premium in pay offers can be observed for language skills, followed by customer service skills, among both female- and male-targeted postings. Some skills seem to be important for women but not for men, and vice versa. For example, while project management skills are significantly rewarded (0.6% to 10.7% premia in wage offers) for women, they have no effect on pay offers for men. In contrast, mentioning social skills requirements in a job ad is associated with a lower wage offer for women and a higher wage offer for men. As shown in Table 8, these patterns do not change when we use the Heckman two-stage procedure.

Due to differences in infrastructure, economic growth, level of competition, and local prices, one might expect pay offers to differ across geographical regions. As seen in Table 7, we observe significant wage offer premia ranging between 2.8 and 8.6 percent for the two largest cities (i.e., Ha Noi and HCM) by comparison with smaller towns. It is possible that the urban wage offer premia stem from agglomeration economies that result in higher labor productivity in large and dense labor markets (Moretti, 2014). The presence of an urban wage offer premium might also be explained by the higher level of competition in urban labor markets, where employers have less wage-setting power over their employees and thus need to offer higher wages than in less competitive labor markets (Hirsch et al., 2022). Results are similar when using the Heckman two-step procedure.

The beauty premium in pay offers could also just be driven by occupational sorting, whereby physical attractiveness is highly rewarded for jobs with high interpersonal interactions. This productivity-enhancing effect of physical attractiveness in those jobs might come from customer/co-worker discrimination—customers' and co-workers' preferences for interacting with more physically attractive workers. With this interpretation, physical attractiveness represents a form of human capital that is beneficial to the firm (Pfann et al., 2000); hence, the estimated beauty premium may merely reflect the productivity-enhancing effect of good looks.

To investigate the productivity-enhancing explanation, we examine how the effect of attractiveness on the wage offer varies between occupations with high and low levels of interpersonal interaction. For this purpose, we take the sum of social, people management, and customer service skill variables—each a discrete variable ranging from 0 to 3—and then construct an indicator variable, *Social_interact*, which is one if that sum is strictly above its median value of one and is zero otherwise.[14]

Figure 3 presents beauty premium estimates for jobs that involve different levels of interpersonal interaction. We observe beauty premia of 3.0% and 4.1% for women in occupations with low and high levels of social interaction, respectively. This finding suggests that good looks can translate into higher pay offer for women not only in jobs with intensive social interactions, where good looks may be explicitly essential for job performance, but also in those where physical attractiveness is not expected to be a productivity-enhancing characteristic. Interestingly, for the subsample of men-targeted job postings, we find a significant negative beauty premium on posted wages in occupations characterized by a high level of interpersonal interactions. In occupations with a low level of social interaction, the effect of looks on wage offers is not statistically significant.

The results remain qualitatively similar when using the Heckman two-step procedure, showing an even higher beauty premium for low-interaction jobs (5.5%) compared to 4.8% for high-interaction jobs.

[Figure 3 here]

4.3 Cultural attitudes towards gender roles

Finally, to investigate the mechanism through which physical attractiveness positively impacts women's wage offers but not men's, we consider the influence of culture-driven gender role attitudes. This concept refers to general sentiments or beliefs about the roles of men and women along various dimensions, such as the division of household labor, occupational segregation, and workplace power. If physical attractiveness plays an important part for women in their traditional social roles, the persistence of gender role attitudes translates into a persistence in how individuals and the market value women's physical attractiveness.

Previous literature documents a regional disparity in gender role attitudes between Northerners and Southerners in Vietnam. That is, people living in the North appear more conservative in their attitudes toward gender norms compared to their Southern

[14]We choose to focus on social, people management, and customer service skills stated in the vacancy as this better reflects the tasks to be performed on the job than do job titles or industry categorizations (Deming and Kahn, 2018).

counterparts (Taylor, 2013; Grosse, 2015). This disparity can be attributed to the different socio-political circumstances experienced by Northerners and Southerners during the Vietnam War, or the greater influence of Confucian norms in the North due to stronger influences from China. If this holds, we should expect the beauty premium for women's pay offers to be more pronounced in jobs located in the North.

To investigate regional disparities in the relationship between wage offers and beauty requirements in job postings, we include in model (2) a *North* indicator variable, which equals unity if a job is located in Northern regions and zero if it is located in Southern regions, and the interaction term $Attractiveness \times North$. Estimation results are summarized in Figure 4. In Panel A, we see a statistically significant beauty premium for women in the Northern region, while no significant premium is observed in the Southern region. This regional disparity in beauty premia suggests that the overall positive impact of physical appearance on women's wage offers is primarily driven by job vacancies located in the North, where people are more conservative toward traditional gender roles. In contrast, our analysis reveals no significant beauty effect on men's wage offers across both regions.

Using the Heckman two-step procedure, we find similar results (Panel B), with the beauty premium for women being stronger in the North at 7.4%, compared to 3.3% in the South. For men, there is a beauty penalty of 4.7% in the Southern region and a beauty premium of 5.5% in the Northern region.

[Figure 4 here]

5 Conclusion

In this paper, we have examined the role of physical attractiveness requirements in wage offers. Empirical estimates of the effect of good looks on actual wages can be biased due to the limited information about the actual job roles of workers who have already been hired. This study overcomes this problem by relying on online postings that contain detailed information on job roles alongside salary offer information.

We employ a well-structured dataset of female- and male-targeted job ads gathered from one of the largest job portals in Vietnam. Beauty-biased word choices and other skill requirements are extracted from the job posting content. In our sample of 38,945 unique gender-targeted job ads, preferences for good looks are present in 10% of men-targeted ads and 29.2% of women-targeted ads. To mitigate the selection bias in estimating the beauty premium, the study first pre-matches jobs by job title and then adopts the state-of-the-art word transformer SBERT to match job postings based on the job ad text.

Our findings indicate a statistically significant beauty premium in wage offers targeted at women, even after controlling for a rich set of jobs' observable characteristics. Physically attractive women are offered, on average, 5% higher salaries, but no beauty effect on pay offers is found for physically attractive men. Additionally, we observe wage offer premia for physically attractive women not only among jobs involving higher levels of social or customer interaction but also among other occupations where physical appearance is not essential for job performance. However, the beauty premium in wage offers to women is only present in ads for jobs requiring little to no work experience and for entry-level jobs. Exploiting the regional disparities in gender role attitudes, we further show clear evidence that traditional social roles serve as a mechanism underlying the gender differences in returns to physical attractiveness.

These results support the body of evidence documenting that physical appearance is more important for women than for men. We can think of two main reasons that might be behind this pattern. First, physical attractiveness plays an important role in women's traditional social roles as wives, homemakers, and caregivers. This perception remains prevalent and continues to have a strong influence on women's labor market prospects. Second, if physical attractiveness in the opposite sex is valued comparatively more by men than it is by women, the simple fact that it is still more common for men to occupy higher-ranking positions which involve salary decisions can translate into higher salaries for physically more attractive women.

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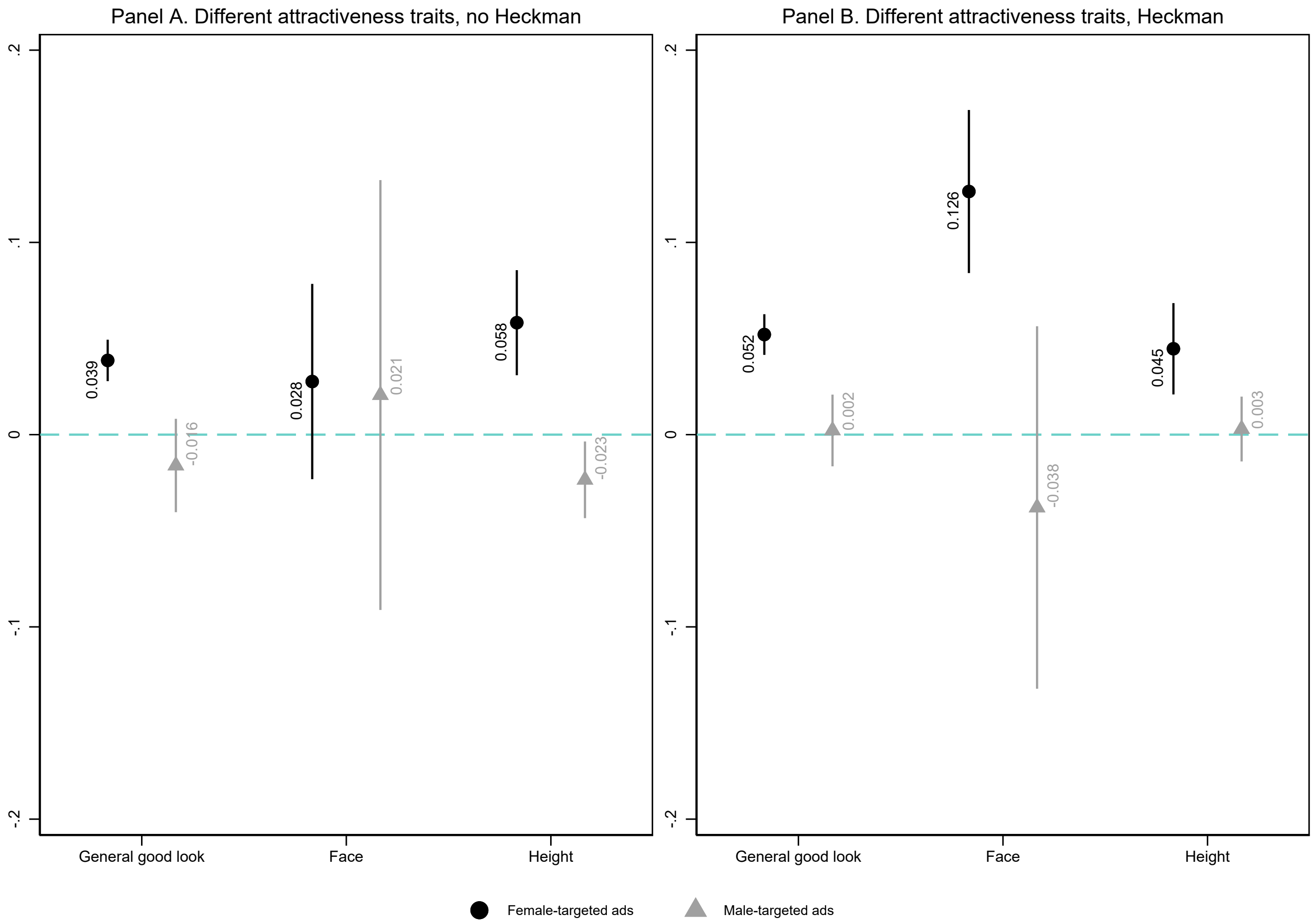
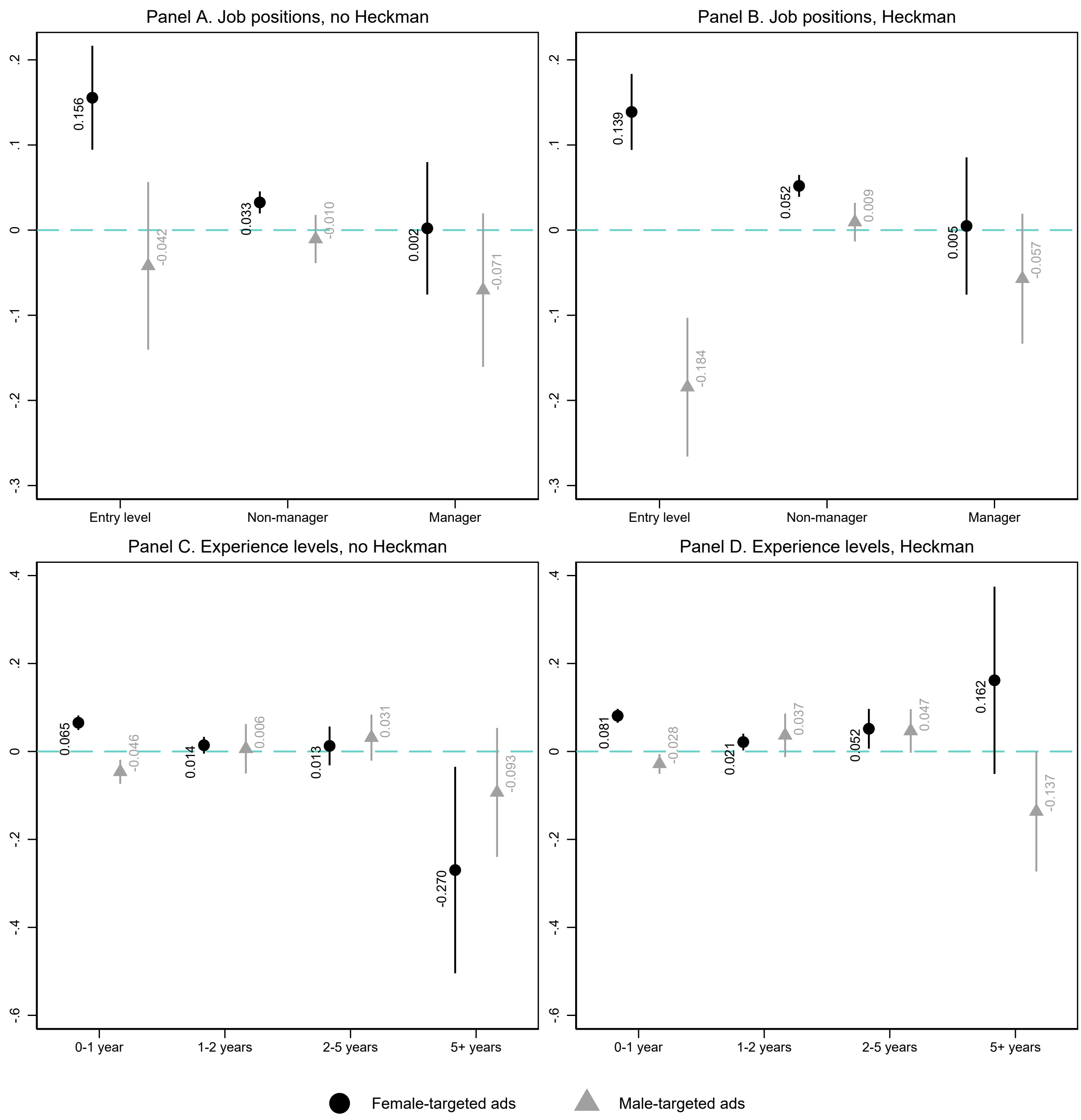
Figure 1: Wage offer premium estimates across physical traits



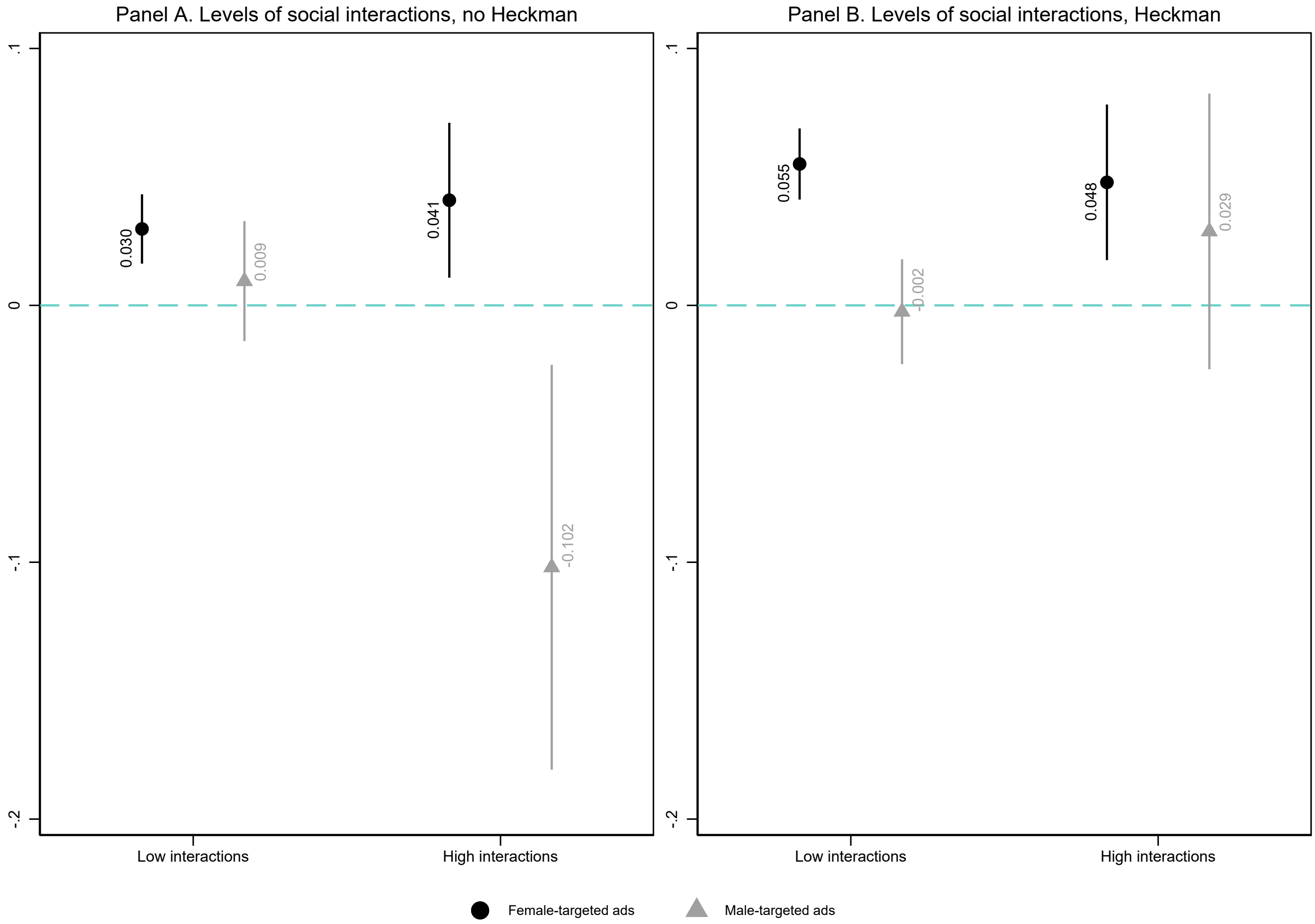
Notes: The figure presents wage offer premium estimates for women and men by physical traits. Estimates with 95% confidence intervals are reported.

Figure 2: Beauty premium estimates across job positions and experience levels



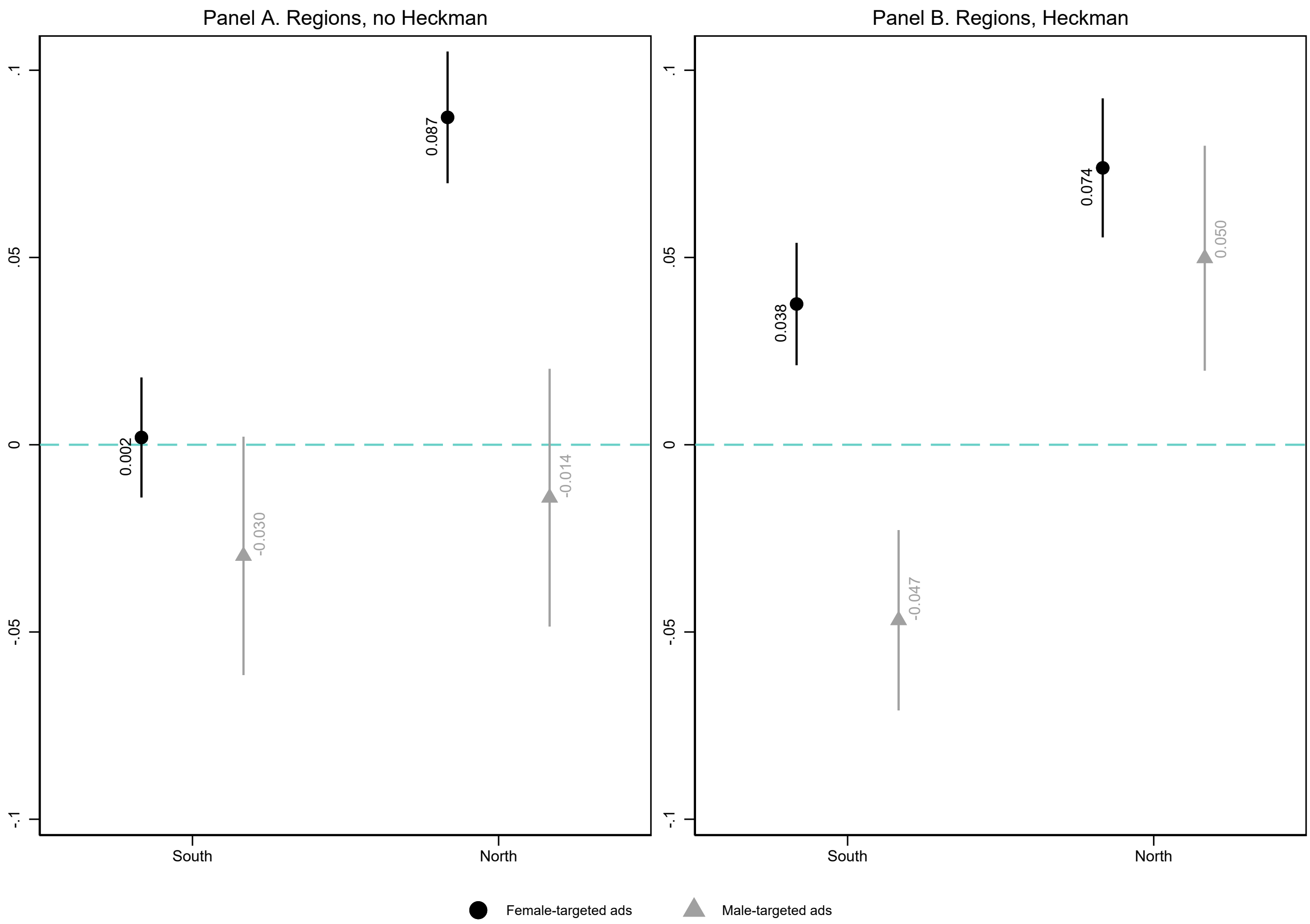
Notes: The figure presents beauty premium estimates for women and men by job positions (Panels A and B) and experience levels (Panels C and D). Estimates with 95% confidence intervals are reported.

Figure 3: Beauty premium estimates for low and high levels of interpersonal interaction



Notes: The figure presents beauty premium estimates for women and men by levels of social interactions without adjusting for selection effects (Panel A) and adjusting for selection effects (Panel B). Estimates with 95% confidence intervals are reported.

Figure 4: Beauty premium estimates for North and South Vietnam



Notes: The figure presents beauty premium estimates for women and men by regions without adjusting for selection effects (Panel A) and adjusting for selection effects (Panel B). Estimates with 95% confidence intervals are reported.

Table 1: Descriptive statistics for the full sample

	(1) ADS WITH SALARY (N = 137,142)	(2) ADS WITH NO SALARY (N = 122,491)	(3) DIFFERENCE
High school	0.040	0.138	-0.098***
Vocational training	0.007	0.005	0.002***
Associate degree	0.570	0.629	-0.059***
University degree	0.378	0.225	0.153***
Other education	0.005	0.003	0.002***
0-1 year	0.250	0.417	-0.167***
1-2 years	0.387	0.343	0.045***
2-5 years	0.299	0.210	0.089***
5+ years	0.064	0.030	0.033***
New entry/Internship	0.033	0.030	0.003***
Non-manager	0.767	0.835	-0.069***
Manager	0.201	0.135	0.066***
Ha Noi	0.253	0.321	-0.067***
Ho Chi Minh City	0.274	0.382	-0.107***
Other cities	0.472	0.298	0.175***
Gender targeting	0.076	0.152	-0.076***
Attractiveness pref.	0.440	0.458	-0.018***

Notes: The table shows the mean values and differences in mean of all variables in two subsamples of job postings explicitly quoting salary and jobs not quoting salary. Columns (1) and (2) report the mean of jobs with salary and jobs without salary subsamples, respectively. Column (3) reports the difference in means between postings with salary and postings without salary subsamples. *, **, and *** indicate significance at 10%, 5%, and 1% for a t-test of whether postings with salary and postings without salary subsamples have equal means, respectively.

Table 2: Proportion of job postings featuring preferences for physical appearance

	(1) ADS WITH SALARY (N = 137,142)	(2) ADS WITH NO SALARY (N = 122,491)
EDUCATION LEVEL		
High school	0.319	0.192
Vocational training	0.084	0.025
Associate degree	0.150	0.087
University degree	0.057	0.049
Other education	0.076	0.059
EXPERIENCE LEVEL		
0-1 year	0.203	0.110
1-2 years	0.152	0.078
2-5 years	0.068	0.056
5+ years	0.039	0.029
JOB POSITION		
New entry/Internship	0.165	0.084
Non-manager	0.165	0.080
Manager	0.069	0.060
LOCATION		
Ha Noi	0.154	0.088
Ho Chi Minh City	0.150	0.064
Other cities	0.154	0.077

Notes: The table shows the proportion of postings featuring physical appearance requirements in two subsamples of postings explicitly quoting salary and jobs not quoting salary in columns (1) and (2), respectively.

Table 3: Descriptive statistics for gender-targeted samples: education, experience, job level

	MALE (N = 23,908)		FEMALE (N = 15,037)		
	(1) MEAN	(2) SD	(3) MEAN	(4) SD	(5) DIFFERENCE
WAGE	8,882,292	5,279,748	7,752,873	4,038,827	1,129,419***
EDUCATION					
High school	0.189	0.391	0.090	0.287	0.098***
Vocational training	0.013	0.114	0.004	0.063	0.009***
Associate degree	0.593	0.491	0.706	0.456	-0.113***
University degree	0.199	0.400	0.198	0.398	0.002
Other education	0.006	0.074	0.002	0.045	0.004***
EXPERIENCE					
0-1 year	0.405	0.491	0.396	0.489	0.009*
1-2 years	0.333	0.471	0.404	0.491	-0.071***
2-5 years	0.224	0.417	0.185	0.389	0.039***
5+ years	0.038	0.192	0.015	0.120	0.023***
LEVEL					
New entry	0.033	0.178	0.042	0.201	-0.009***
Employee	0.847	0.360	0.887	0.316	-0.040***
Manager	0.120	0.325	0.070	0.243	0.050***

Notes: The table shows summary statistics of wage, education, experience, and job level variables. Columns (1) and (3) report the mean of male and female subsamples, respectively. Columns (2) and (4) report the standard deviation of male and female subsamples, respectively. Column (5) reports the difference in means between male and female subsamples. *, **, and *** indicate significance at 10%, 5%, and 1% for a t-test of whether male and female subsamples have equal means, respectively.

Table 4: Descriptive statistics for gender-targeted samples: location, skills

	Male (N = 23,908)		Female (N = 15,037)		
	(1) Mean	(2) SD	(3) Mean	(4) SD	(5) Difference
Location					
Ha Noi	0.275	0.446	0.346	0.476	-0.072***
Ho Chi Minh City	0.357	0.479	0.367	0.482	-0.010**
Other cities	0.368	0.482	0.287	0.452	0.082***
Skills					
Computer	0.277	0.448	0.525	0.499	-0.248***
Software	0.179	0.384	0.162	0.368	0.017***
Financial	0.068	0.251	0.335	0.472	-0.267***
People management	0.029	0.168	0.035	0.183	-0.006***
Project management	0.103	0.304	0.076	0.266	0.027***
Artistic	0.090	0.286	0.042	0.200	0.048***
Language	0.175	0.380	0.306	0.461	-0.131***
Character	0.797	0.402	0.862	0.346	-0.064***
Cognitive	0.255	0.436	0.290	0.454	-0.036***
Customer service	0.183	0.387	0.263	0.440	-0.080***
Social	0.406	0.491	0.466	0.499	-0.060***
Writing	0.026	0.158	0.028	0.166	-0.003
Physical attr./ness	0.103	0.304	0.292	0.455	-0.189***

Notes: The table shows summary statistics of job location and skill variables. Columns (1) and (3) report the mean of male and female subsamples, respectively. Columns (2) and (4) report the standard deviation of male and female subsamples, respectively. Column (5) reports the difference in means between male and female subsamples. *, **, and *** indicate significance at 10%, 5%, and 1% for a t-test of whether male and female subsamples have equal means, respectively.

Table 5: Frequency of stating preferences for physical appearance among subsamples

	(1)	(2)	(3)
	MALE (N=23,908)	**FEMALE (N=15,037)**	**DIFFERENCE**
EDUCATION			
High school	0.144	0.594	-0.450***
Vocational training	0.051	0.186	-0.135***
Associate degree	0.113	0.297	-0.184***
University degree	0.042	0.143	-0.100***
Other education	0.053	0.100	-0.047
EXPERIENCE			
0-1 year	0.195	0.309	-0.113***
1-2 years	0.037	0.355	-0.318***
2-5 years	0.048	0.136	-0.088***
5+ years	0.031	0.103	-0.072***
LEVEL			
New entry/Internship	0.197	0.285	-0.087***
Non-manager	0.109	0.305	-0.196***
Manager	0.040	0.134	-0.094***
LOCATION			
Ha Noi	0.112	0.267	-0.154***
Ho Chi Minh City	0.096	0.310	-0.214***
Other cities	0.103	0.300	-0.197***

Notes: The table shows the frequency of stating physical appearance requirements and mean wage by different subsamples of education, job levels, experience levels, and job locations for men-targeted ads in column (1) and for women-targeted ads in column (2). Column (3) reports the difference in means between men and women subsamples. *, **, and *** indicate significance at 10%, 5%, and 1% for a t-test of whether men and women subsamples have equal means, respectively.

Table 6: Probit regression results for stating preferences for physical appearance

	(1)	(2)
	FEMALE	MALE
Vocational training	-0.095***	-0.059***
	(0.035)	(0.011)
Associate degree	-0.057***	-0.050***
	(0.012)	(0.006)
University degree	-0.052***	-0.047***
	(0.015)	(0.008)
Other education	-0.107*	-0.024
	(0.059)	(0.021)
1-2 years	0.045***	-0.026***
	(0.007)	(0.004)
2-5 years	0.033***	-0.002
	(0.010)	(0.005)
5+ years	-0.023	-0.019**
	(0.031)	(0.010)
Non-manager	-0.002	0.000
	(0.015)	(0.007)
Manager	-0.140***	0.019
	(0.025)	(0.012)
Ha Noi	-0.014*	0.026***
	(0.007)	(0.004)
HCM	0.012*	0.005
	(0.007)	(0.003)
Computer	0.003	-0.016***
	(0.007)	(0.004)
Software	-0.097***	-0.008
	(0.010)	(0.005)
Language	-0.049***	-0.012**
	(0.008)	(0.005)
Financial	-0.005	0.026***
	(0.009)	(0.009)
People management	0.044**	-0.001
	(0.018)	(0.009)
Project management	0.023*	-0.026***
	(0.012)	(0.006)
Art	0.043***	-0.005
	(0.016)	(0.006)
Character	0.060***	0.032***
	(0.010)	(0.006)

Table 6: Probit regression results for stating preferences for physical appearance

	(1)	(2)
Cognitive	-0.017**	0.028***
	(0.007)	(0.004)
Customer service	-0.011	-0.019***
	(0.008)	(0.004)
Social	0.082***	0.065***
	(0.007)	(0.003)
Writing	0.018	-0.041***
	(0.019)	(0.011)
Obs.	14,601	22,940

Notes: The table presents the results of Probit models for job characteristics/requirements of ads stating physical appearance preferences. Column (1) shows the average marginal effect for the female subsample. Column (2) shows the average marginal effect for the male subsample. The dependent variable is an indicator for whether a vacancy mentions preferences for physical appearance. Time, industry, job title, and firm size indicators are included but not reported. Robust standard errors are shown in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Table 7: Beauty premium estimates for posted wages without adjusting for selection effects

	FEMALE-TARGETED ADS			MALE-TARGETED ADS		
	(1) NO MATCHING	(2) TEXT MATCHING	(3) CEM	(4) NO MATCHING	(5) TEXT MATCHING	(6) CEM
Phys. attractiveness	0.052***	0.037***	0.043***	-0.005	-0.017	-0.026
	(0.007)	(0.006)	(0.011)	(0.008)	(0.014)	(0.020)
Vocational training	0.156***	0.127***		-0.041***	0.184***	0.143**
	(0.039)	(0.049)		(0.013)	(0.031)	(0.068)
Associate degree	-0.027***	0.004	-0.010	-0.009	0.026***	0.034
	(0.009)	(0.009)	(0.023)	(0.006)	(0.009)	(0.031)
University degree	0.059***	0.047***	0.126***	0.139***	0.024	0.176***
	(0.011)	(0.014)	(0.032)	(0.009)	(0.023)	(0.047)
Other education	0.010	0.018		0.052*	-0.123**	
	(0.037)	(0.111)		(0.028)	(0.051)	
1-2 years	0.077***	0.085***	0.079***	0.039***	0.069***	0.070**
	(0.005)	(0.006)	(0.011)	(0.005)	(0.016)	(0.030)
2-5 years	0.292***	0.299***	0.272***	0.184***	0.157***	0.137***
	(0.008)	(0.014)	(0.026)	(0.006)	(0.019)	(0.037)
5+ years	0.573***	0.781***	0.733	0.431***	0.408***	0.329***
	(0.032)	(0.067)	(0.504)	(0.016)	(0.051)	(0.065)
Non-manager	0.071***	0.066***	0.029	-0.010	0.044***	-0.048*
	(0.010)	(0.016)	(0.044)	(0.011)	(0.016)	(0.028)
Manager	0.447***	0.352***	0.401***	0.240***	0.307***	0.315***
	(0.022)	(0.031)	(0.097)	(0.014)	(0.057)	(0.075)
Ha Noi	0.037***	-0.011	0.038**	0.057***	0.057***	0.016
	(0.006)	(0.008)	(0.016)	(0.005)	(0.010)	(0.021)
HCM	0.084***	0.054***	0.086***	0.059***	0.028***	-0.045**
	(0.006)	(0.008)	(0.015)	(0.004)	(0.011)	(0.018)
Computer	-0.028***	0.013*	-0.013	-0.030***	-0.054***	-0.024
	(0.005)	(0.007)	(0.012)	(0.005)	(0.014)	(0.022)
Software	-0.019***	0.030**	0.003	0.044***	-0.008	-0.002
	(0.007)	(0.014)	(0.018)	(0.006)	(0.025)	(0.031)
Language	0.116***	0.099***	0.083***	0.120***	0.095***	0.141***

Table 7: Beauty premium estimates for posted wages without adjusting for selection effects

	FEMALE-TARGETED ADS			MALE-TARGETED ADS		
	(0.006)	(0.010)	(0.013)	(0.006)	(0.019)	(0.026)
Financial	0.019***	-0.064***	-0.038**	0.138***	0.078*	0.130***
	(0.007)	(0.008)	(0.015)	(0.009)	(0.044)	(0.048)
People management	-0.018	0.043**	-0.050	0.109***	-0.083*	-0.075
	(0.014)	(0.017)	(0.032)	(0.017)	(0.050)	(0.049)
Project management	0.064***	0.060***	0.107***	-0.047***	-0.018	0.042
	(0.010)	(0.015)	(0.026)	(0.007)	(0.029)	(0.030)
Art	0.042***	-0.054***	0.004	0.041***	0.023	-0.001
	(0.014)	(0.017)	(0.028)	(0.007)	(0.021)	(0.025)
Character	-0.070***	-0.025**	-0.041**	-0.049***	-0.043**	-0.067***
	(0.007)	(0.010)	(0.017)	(0.005)	(0.021)	(0.025)
Cognitive	0.022***	0.022***	0.011	-0.023***	-0.042***	-0.020
	(0.005)	(0.008)	(0.013)	(0.005)	(0.016)	(0.021)
Customer service	-0.004	0.053***	0.052***	0.075***	0.005	0.034
	(0.006)	(0.009)	(0.014)	(0.007)	(0.019)	(0.024)
Social	0.009*	-0.048***	-0.005	0.032***	0.044***	0.023
	(0.005)	(0.007)	(0.012)	(0.005)	(0.013)	(0.020)
Writing	-0.005	-0.003	0.012	0.089***	0.095	-0.054
	(0.011)	(0.018)	(0.027)	(0.014)	(0.061)	(0.065)
Obs.	15,027	7,807	3,050	23,905	4,480	1,370
R^2	0.539	0.491	0.417	0.571	0.671	0.654

Notes: The table presents beauty premium estimates for women and men. Columns (1) and (4) show results for the whole sample without matching for female and male subsamples, respectively. Columns (2) and (5) show results for text matching for female and male subsamples, respectively. Columns (3) and (6) show results from CEM for female and male subsamples, respectively. Robust standard errors are shown in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Table 8: Beauty premium estimates for posted wages from Heckman second stage regression

	FEMALE-TARGETED ADS			MALE-TARGETED ADS		
	(1) NO MATCHING	(2) TEXT MATCHING	(3) CEM	(4) NO MATCHING	(5) TEXT MATCHING	(6) CEM
Phys. attractiveness	0.052***	0.054***	0.027**	-0.002	-0.002	-0.013
	(0.007)	(0.006)	(0.012)	(0.008)	(0.011)	(0.021)
Vocational training	0.160***	0.437***		-0.031**	-0.122***	0.166**
	(0.039)	(0.089)		(0.013)	(0.032)	(0.068)
Associate degree	-0.023***	-0.003	0.020	-0.007	0.040***	0.063**
	(0.009)	(0.008)	(0.020)	(0.006)	(0.008)	(0.031)
University degree	0.063***	0.064***	0.119***	0.143***	0.149***	0.235***
	(0.011)	(0.014)	(0.033)	(0.009)	(0.024)	(0.055)
Other education	0.015	-0.114		0.055**	0.063	
	(0.037)	(0.108)		(0.028)	(0.044)	
1-2 years	0.075***	0.067***	0.064***	0.040***	0.070***	0.088***
	(0.005)	(0.006)	(0.012)	(0.005)	(0.017)	(0.033)
2-5 years	0.290***	0.241***	0.261***	0.184***	0.136***	0.157***
	(0.008)	(0.013)	(0.027)	(0.006)	(0.017)	(0.039)
5+ years	0.571***	0.491***		0.435***	0.365***	0.369***
	(0.032)	(0.046)		(0.016)	(0.043)	(0.067)
Non-manager	0.073***	0.047***	0.026	-0.010	0.013	-0.043
	(0.010)	(0.012)	(0.050)	(0.011)	(0.014)	(0.029)
Manager	0.449***	0.338***	0.312***	0.239***	0.341***	0.338***
	(0.022)	(0.035)	(0.097)	(0.014)	(0.051)	(0.077)
Ha Noi	0.037***	0.035***	0.021	0.056***	0.039***	0.064***
	(0.006)	(0.008)	(0.017)	(0.005)	(0.011)	(0.021)
HCM	0.083***	0.083***	0.089***	0.059***	0.054***	-0.008
	(0.006)	(0.008)	(0.017)	(0.004)	(0.010)	(0.020)
Computer	-0.028***	-0.018**	-0.007	-0.030***	-0.047***	-0.043*
	(0.005)	(0.007)	(0.013)	(0.005)	(0.016)	(0.022)
Software	-0.019***	0.013	0.016	0.044***	0.144***	0.053
	(0.007)	(0.014)	(0.018)	(0.006)	(0.022)	(0.033)
Language	0.115***	0.094***	0.117***	0.119***	0.115***	0.113***

Table 8: Beauty premium estimates for posted wages from Heckman second stage regression

	Female-targeted ads			Male-targeted ads		
	(0.006)	(0.010)	(0.015)	(0.006)	(0.019)	(0.028)
Financial	0.019***	0.048***	-0.039***	0.135***	-0.056	0.078
	(0.007)	(0.008)	(0.014)	(0.009)	(0.041)	(0.054)
People management	-0.018	0.032	-0.013	0.109***	-0.070*	-0.089*
	(0.014)	(0.020)	(0.031)	(0.017)	(0.040)	(0.051)
Project management	0.064***	0.056***	0.109***	-0.043***	0.022	0.047
	(0.010)	(0.017)	(0.025)	(0.007)	(0.024)	(0.034)
Art	0.041***	0.046**	-0.016	0.040***	0.028	-0.033
	(0.014)	(0.020)	(0.028)	(0.007)	(0.019)	(0.029)
Character	-0.069***	-0.010	-0.036**	-0.048***	-0.039**	-0.058**
	(0.007)	(0.011)	(0.017)	(0.005)	(0.020)	(0.027)
Cognitive	0.021***	0.005	0.005	-0.022***	-0.060***	-0.018
	(0.005)	(0.009)	(0.014)	(0.005)	(0.013)	(0.023)
Customer service	-0.003	0.045***	0.033**	0.076***	0.003	0.022
	(0.006)	(0.010)	(0.015)	(0.007)	(0.018)	(0.026)
Social	0.009	-0.010	-0.004	0.031***	0.014	0.016
	(0.005)	(0.008)	(0.013)	(0.005)	(0.011)	(0.020)
Writing	-0.005	0.022	-0.035	0.090***	-0.017	-0.076
	(0.011)	(0.024)	(0.029)	(0.014)	(0.047)	(0.057)
IMR	-0.025***	-0.013*	-0.012	-0.042***	-0.018**	-0.167***
	(0.005)	(0.007)	(0.026)	(0.005)	(0.009)	(0.046)
Obs.	15,027	7,830	2,530	23,905	4,425	1,200
R^2	0.540	0.477	0.409	0.572	0.662	0.685

Notes: The table presents beauty premium estimates for women and men in the second stage of the Heckman procedure controlling for selection bias. Columns (1) and (4) show results for the whole sample without matching for female and male subsamples, respectively. Columns (2) and (5) show results for text matching for female and male subsamples, respectively. Columns (3) and (6) show results from CEM for female and male subsamples, respectively. Robust standard errors are shown in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Online Appendix

A1 Covariate balance diagnostics for CEM

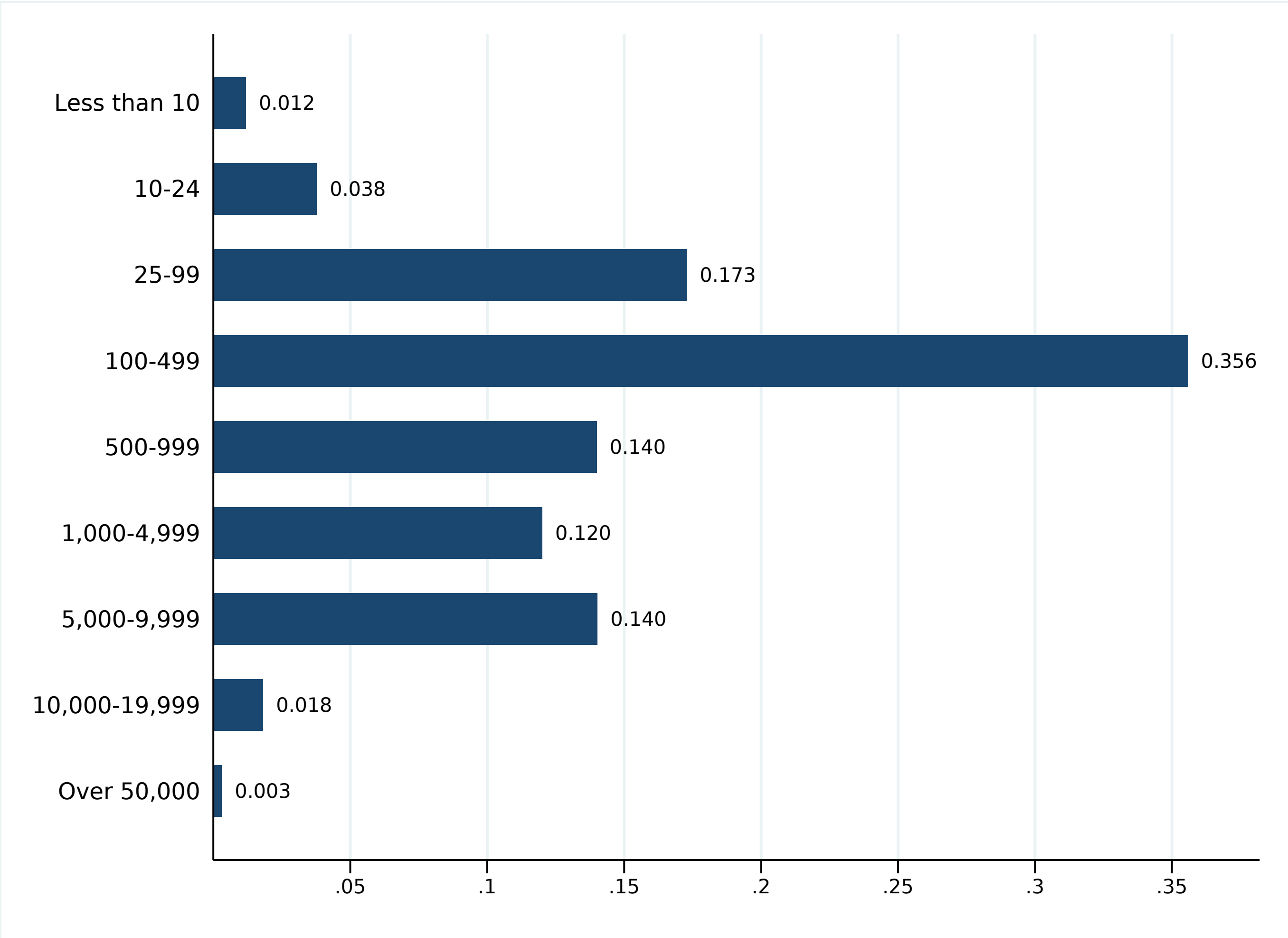
Table A9 shows the extent of covariate imbalance after CEM. The overall imbalance is illustrated by the L1 statistic, which represents the percentage of overlap between the density of the two distributions of treated and control groups. The value of zero (i.e., L1 = 0) indicates perfect global balance, higher values indicate a higher imbalance between treatment and control units, and the maximum value of one indicates complete separation. We observe a substantial reduction in the L1 statistic after matching, from 0.814 to 0.045 for the women subsample and from 0.918 to 0.053 for the men's subsample; i.e., our matching strategy leads to an overall increase in covariate balance. The amount of covariate imbalance remaining is trivial.

We also report unidimensional measures of imbalance computed for each variable separately. As can be seen, our matchings for both women and men subsamples achieve perfect balance in the means, marginal and joint distributions of almost all job characteristics. The only exception is the job title, where the imbalance remains at negligible levels.

A2 Posting frequency

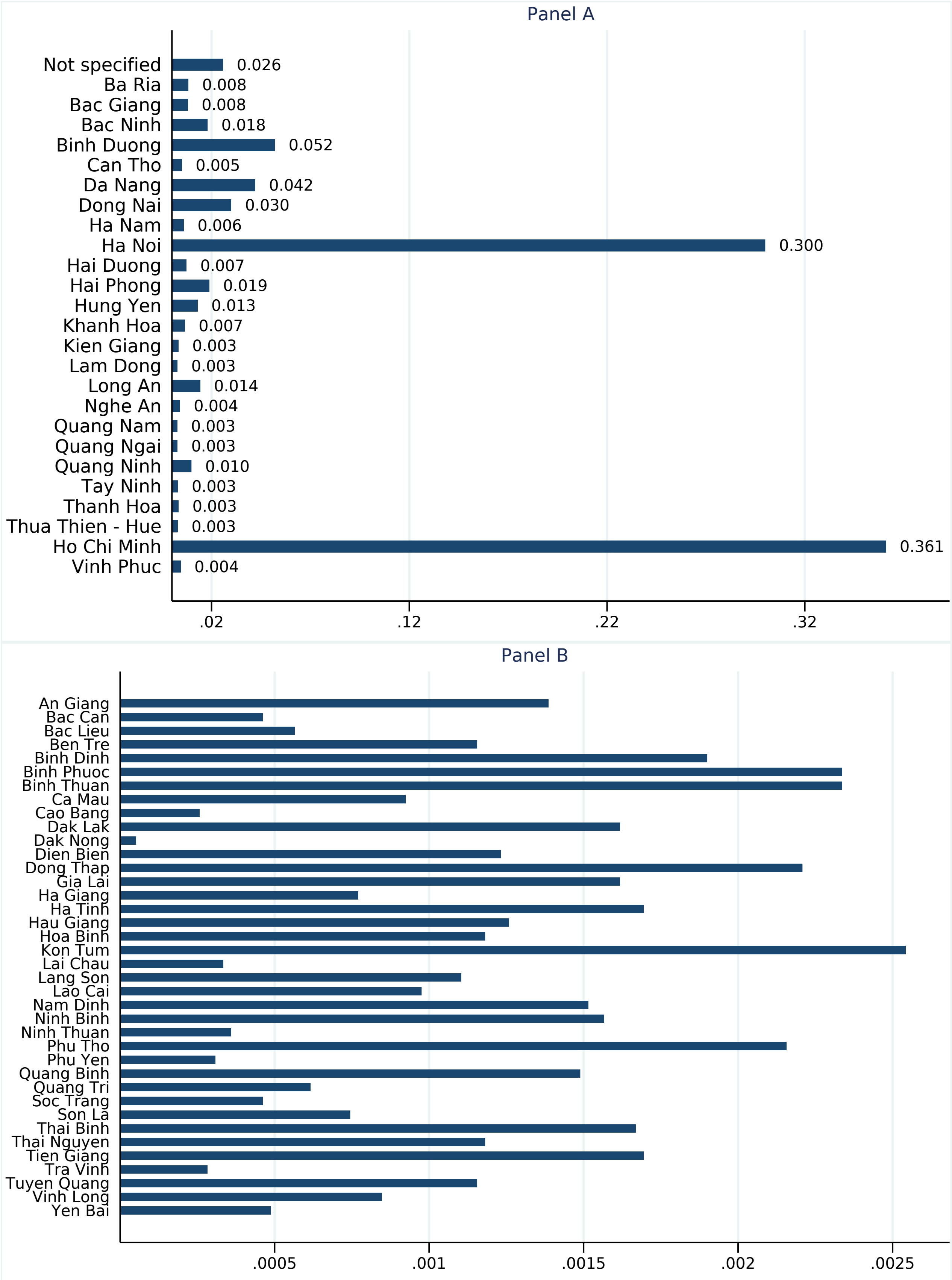
In Appendix Figure A4, we examine whether the observed beauty premium is driven by the potential influence of employers' posting practices. The concern is that employers who engage in frequent and extensive job postings, as proxied by the number of job postings made by each employer during the sample period, may have less tailored and specific vacancy descriptions. The results reveal that, irrespective of whether vacancies are posted by employers with frequent or infrequent posting patterns, we still see a significant beauty premium for women's wages. Specifically, we find beauty premia of 3.4% and 3.9% for women in jobs advertised by frequently (above-median) and infrequently (below-median) posting employers, respectively.

Figure A1: Share of job postings by firm size



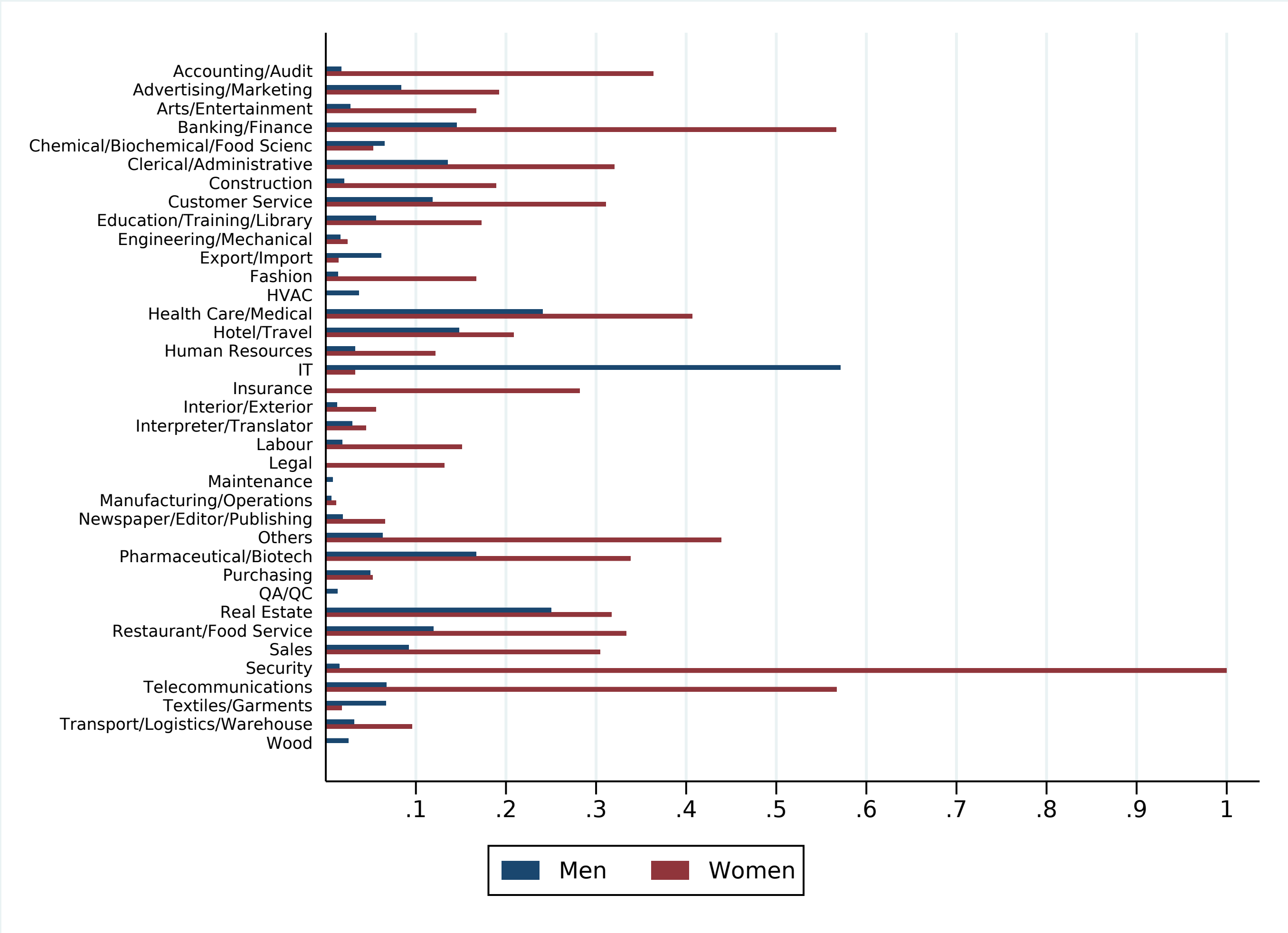
Notes: The figure shows the share of vacancies by firm size categories as measured by the number of employees of the recruiting firm.

Figure A2: Share of job postings by location



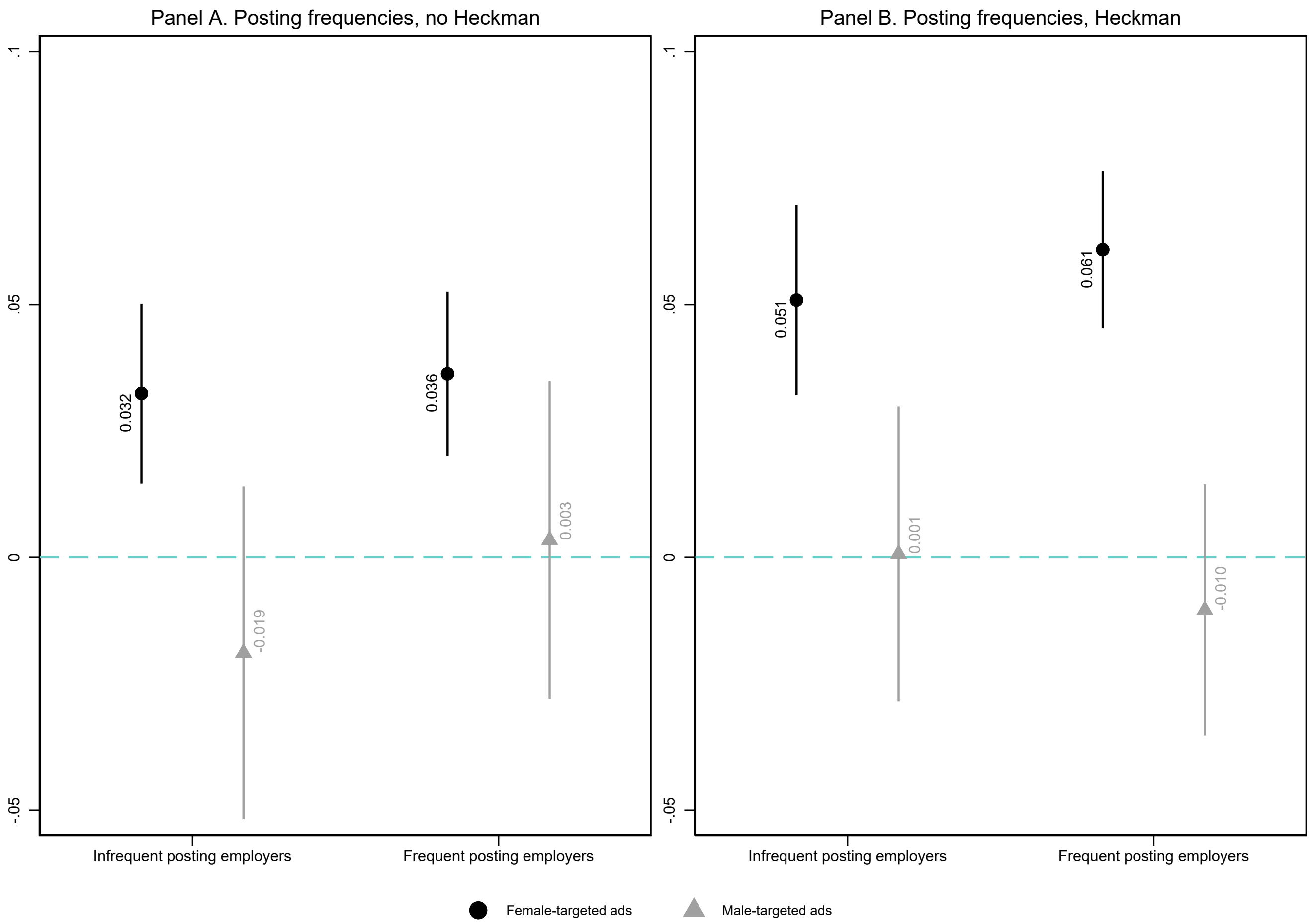
Notes: Panel A shows the share of vacancies by job locations which have at least 100 job postings. Panel B shows the share of vacancies by job locations which have less than 100 job postings.

Figure A3: Frequency of stating preferences for physical appearance by industry, for men's jobs versus women's jobs



Notes: The figure shows the share of beauty-biased ads by industry in male-targeted ads (blue bars) and female-targeted ads (red bars).

Figure A4: Beauty premium estimates by posting frequency



Notes: The figure presents beauty premium estimates for women and men by posting frequencies without adjusting for selection effects (Panel A) and adjusting for selection effects (Panel B). Estimates with 95% confidence intervals are reported.

Table A1: List of job titles/occupations

Accountant	Driver	PR staff
Accounting manager	Editor	Primary school teacher
Actor	Engineer	Procedure controller
Admin	English interpreter	Product advisor
Appraiser	English teacher	Product/content reviewer
Architect	Equipment deployment staff	Production statistics staff
Art teacher	Event organizer	Project development staff
Bartender	Financial advisor	QA staff
Beauty teacher	Gymnastics teacher	Real estate businessman
Beauty technician	HR staff	Receptionist
Bodyguard	Import-export staff	Restaurant manager
Branch manager	Internal auditor	Sale assistant
Broker	IT staff	Sales
Business representative	IT teacher	Sales consultant
Business support staff	Legal experts	Sales manager
Businessman	Librarian	Secretary
Cashier	Live streamer	Security
Chef	Manager	Shop manager
Chess game instructor	Marketing staff	Spa advisor
Chinese interpreter	Marketing manager	Stylist
Clearance specialist	Maths teacher	Supply chain staff
Content creator	MC	Support staff
Controller/supervisor	Merchandiser	Swimming pool lifeguard
Cook	Network admin	Teaching assistant
Customer service manager	Nurse	Technician
Customer service staff	Nursery teacher	Tour operator
Deliveryman	Office supporter	Training specialist
Deputy	Officer	Visa/study abroad advisor
Deputy manager	Online supporter	Waiter
Designer	Others	Warehouse staff
Developer	Partnership staff	Workman
Director	Personal trainer	
Doctor	Pharmacist	

Notes: The table presents the job titles/occupations in our data.

Table A2: List of keywords

SKILLS	KEYWORDS
Art	Art, artistic
Character	Organized, detail-oriented, multitasking, time management, meeting deadlines, energetic
Cognitive	Problem-solving, research, analytical, critical thinking, math, statistics
Computer	Computer, spreadsheets, common software (e.g., Microsoft Excel, PowerPoint)
Customer service	Customer, sales, client, customer service
Financial	Budgeting, accounting, finance, cost
Language	English, Japanese, Korean, Chinese, foreign language
Project management	Project management
People management	Supervisory, leadership, human management, mentoring staff
Social	Communication, teamwork, collaboration, negotiation, presentation
Software	Programming language or specialized software (e.g., Java, SQL, C++)
Writing	Writing
Physical attractiveness	Pretty face, attractive face, good looking, pretty, attractive

Notes: The table presents the categorization of keywords into skill/requirement groups.

Table A3: Descriptive statistics for salary-quoting job subsamples

	(1)	(2)	(3)	(4)	(5)	(6)
	NO GENDER	GENDER	DIFF.	NO PHYS. APPEARANCE	PHYS. APPEARANCE	DIFF.
SALARY	9,634,132	8,446,213	1,187,919***	9,606,251	7,574,860	2,031,391***
EDUCATION						
High school	0.133	0.151	-0.017***	0.111	0.290	-0.179***
Voc. training	0.003	0.010	-0.006***	0.006	0.003	0.003***
Ass. degree	0.626	0.637	-0.011***	0.630	0.621	0.009**
Univ. degree	0.235	0.199	0.036***	0.250	0.085	0.165***
Other educ.	0.002	0.004	-0.002***	0.003	0.001	0.002***
EXPERIENCE						
0-1 year	0.423	0.401	0.022***	0.392	0.557	-0.165***
1-2 years	0.336	0.360	-0.025***	0.343	0.341	0.002
2-5 years	0.211	0.209	0.002	0.231	0.094	0.137***
5+ years	0.031	0.029	0.001	0.034	0.008	0.026***
LEVEL						
New/Intern.	0.027	0.037	-0.009***	0.029	0.032	-0.003**
Non-manager	0.825	0.863	-0.038***	0.823	0.906	-0.084***
Manager	0.148	0.101	0.047***	0.148	0.061	0.087***
LOCATION						
Ha Noi	0.282	0.337	-0.054***	0.297	0.300	-0.003
Ho Chi Minh C.	0.328	0.302	0.026***	0.320	0.324	-0.004
Other cities	0.390	0.361	0.029***	0.383	0.376	0.007*
Obs.	98,197	38,945		116,250	20,892	

Notes: The table shows the summary statistics of main variables across subsamples. *, **, and *** indicate significance at 10%, 5%, and 1% for a t-test of whether the subsamples have equal means, respectively.

Table A4: Correlation matrix

	Attr.	Educ.	Exp.	Level	Comp.	Soft,	Lang,	Fin.	People	Proj.	Art	Char.	Cogn.	Cust.	Soc.
Education	-0.130														
Experience	-0.164	0.427													
Level	-0.097	0.245	0.421												
Computer	0.050	0.158	0.106	0.016											
Software	-0.136	0.252	0.236	0.061	0.230										
Language	-0.115	0.311	0.163	0.101	0.148	0.067									
Financial	0.143	0.020	0.078	-0.028	0.247	0.123	-0.093								
People Mgmt.	-0.029	0.148	0.177	0.230	0.055	0.062	0.028	-0.007							
Project Mgmt.	-0.076	0.195	0.236	0.280	0.126	0.118	0.059	-0.026	0.150						
Art	-0.052	0.072	0.078	0.043	0.016	0.132	0.000	-0.032	0.022	0.055					
Character	0.154	-0.149	-0.150	-0.096	0.063	-0.062	-0.136	0.039	0.001	0.017	0.011				
Cognitive	-0.089	0.224	0.227	0.131	0.164	0.195	0.109	0.046	0.131	0.250	0.153	0.107			
Customer	-0.041	0.082	0.023	0.066	0.062	-0.044	0.095	-0.105	0.022	0.133	0.087	0.101	0.142		
Social	0.159	0.035	-0.045	0.014	0.037	-0.060	0.203	-0.114	0.043	0.082	0.031	0.138	0.133	0.258	
Writing	-0.033	0.066	0.019	-0.004	0.010	0.004	0.052	-0.033	0.036	0.000	0.015	0.051	0.046	0.137	0.016

Notes: The table shows the Spearman correlation coefficients for skill requirement variables.

Table A5: Definitions of main variables

VARIABLE	DEFINITION
High school	An indicator variable that takes the value of 1 if the job ad requires a high school qualification and 0 otherwise.
Vocational training	An indicator variable that takes the value of 1 if the job ad requires a vocational training qualification and 0 otherwise.
Associate degree	An indicator variable that takes the value of 1 if the job ad requires an associate degree qualification and 0 otherwise.
University degree	An indicator variable that takes the value of 1 if the job ad requires a university degree qualification and 0 otherwise.
Other education	An indicator variable that takes the value of 1 if the job ad requires other educational qualifications and 0 otherwise.
0-1 year	An indicator variable that takes the value of 1 if the job ad requires less than one year of experience and 0 otherwise.
1-2 years	An indicator variable that takes the value of 1 if the job ad requires 1-2 years of experience and 0 otherwise.
2-5 years	An indicator variable that takes the value of 1 if the job ad requires 2-5 years of experience and 0 otherwise.
5+ years	An indicator variable that takes the value of 1 if the job ad requires more than 5 years of experience and 0 otherwise.
Entry level/Internship	An indicator variable that takes the value of 1 if the job ad is at an entry level/internship position and 0 otherwise.
Non-manager	An indicator variable that takes the value of 1 if the job ad is at a non-managerial position and 0 otherwise.
Manager	An indicator variable that takes the value of 1 if the job ad is at a managerial position and 0 otherwise.
Ha Noi	An indicator variable that takes the value of 1 if the job ad is located in Ha Noi and 0 otherwise.
HCM	An indicator variable that takes the value of 1 if the job ad is located in HCM city and 0 otherwise.
Other locations	An indicator variable that takes the value of 1 if the job ad is located in other cities/provinces and 0 otherwise.
Computer	An indicator variable that takes the value of 1 if the job ad requires computer skill and 0 otherwise.
Software	An indicator variable that takes the value of 1 if the job ad requires software skill and 0 otherwise.
Language	An indicator variable that takes the value of 1 if the job ad requires language skill and 0 otherwise.
Financial	An indicator variable that takes the value of 1 if the job ad requires financial skill and 0 otherwise.

Table A5: Definitions of main variables

VARIABLE	DEFINITION
People management	An indicator variable that takes the value of 1 if the job ad requires people management skill and 0 otherwise.
Project management	An indicator variable that takes the value of 1 if the job ad requires project management skill and 0 otherwise.
Art	An indicator variable that takes the value of 1 if the job ad requires artistic skill and 0 otherwise.
Character	An indicator variable that takes the value of 1 if the job ad requires character skill and 0 otherwise.
Cognitive	An indicator variable that takes the value of 1 if the job ad requires cognitive skill and 0 otherwise.
Customer service	An indicator variable that takes the value of 1 if the job ad requires customer service skill and 0 otherwise.
Social	An indicator variable that takes the value of 1 if the job ad requires social skill and 0 otherwise.
Writing	An indicator variable that takes the value of 1 if the job ad requires writing skill and 0 otherwise.
Phys. attractiveness	An indicator variable that takes the value of 1 if the job ad requires physical attractiveness and 0 otherwise.

Notes: The table presents definitions of the main variables used in our analysis.

Table A6: Robustness check for beauty premium estimates controlling for height and age requirements

	FEMALE		MALE	
	(1) HEIGHT	(2) HEIGHT AND AGE	(3) HEIGHT	(4) HEIGHT AND AGE
Physical attractiveness	0.032***	0.032***	-0.012	-0.015
	(0.006)	(0.006)	(0.015)	(0.014)
Vocational training	0.134***	0.133***	0.185***	0.159***
	(0.049)	(0.049)	(0.030)	(0.031)
Associate degree	0.005	0.005	0.026***	0.032***
	(0.009)	(0.009)	(0.009)	(0.009)
University degree	0.046***	0.046***	0.024	0.027
	(0.014)	(0.014)	(0.023)	(0.023)
Other education	0.021	0.021	-0.123**	-0.132**
	(0.110)	(0.110)	(0.051)	(0.052)
1-2 years	0.087***	0.087***	0.067***	0.058***
	(0.007)	(0.007)	(0.016)	(0.016)
2-5 years	0.302***	0.302***	0.156***	0.158***
	(0.014)	(0.014)	(0.018)	(0.018)
5+ years	0.787***	0.786***	0.407***	0.399***
	(0.067)	(0.067)	(0.051)	(0.051)
Non-manager	0.065***	0.065***	0.044***	0.052***
	(0.016)	(0.016)	(0.016)	(0.016)
Manager	0.344***	0.344***	0.308***	0.310***
	(0.032)	(0.032)	(0.057)	(0.056)
Ha Noi	-0.011	-0.011	0.057***	0.055***
	(0.008)	(0.008)	(0.010)	(0.010)
HCM	0.055***	0.054***	0.032***	0.031***
	(0.008)	(0.008)	(0.011)	(0.011)
Height	0.062***	0.062***	-0.025**	-0.027**
	(0.016)	(0.016)	(0.012)	(0.012)
Age requirement		0.003		0.075***
		(0.008)		(0.015)
Computer	0.014*	0.014*	-0.055***	-0.060***
	(0.007)	(0.007)	(0.014)	(0.014)
Software	0.031**	0.031**	-0.007	-0.000
	(0.014)	(0.014)	(0.025)	(0.025)
Language	0.100***	0.100***	0.092***	0.095***
	(0.010)	(0.010)	(0.019)	(0.019)
Financial	-0.066***	-0.067***	0.080*	0.067

Table A6: Robustness check for beauty premium estimates controlling for height and age requirements

	FEMALE		MALE	
	(0.008)	(0.008)	(0.044)	(0.045)
People management	0.046***	0.046***	-0.084*	-0.094*
	(0.017)	(0.017)	(0.050)	(0.050)
Project management	0.060***	0.059***	-0.019	-0.025
	(0.015)	(0.015)	(0.029)	(0.029)
Art	-0.055***	-0.055***	0.022	0.033
	(0.017)	(0.017)	(0.021)	(0.021)
Character	-0.024**	-0.024**	-0.044**	-0.033
	(0.010)	(0.010)	(0.021)	(0.020)
Cognitive	0.023***	0.023***	-0.043***	-0.043***
	(0.008)	(0.008)	(0.016)	(0.016)
Customer service	0.056***	0.056***	0.004	0.005
	(0.009)	(0.009)	(0.019)	(0.019)
Social	-0.047***	-0.047***	0.049***	0.053***
	(0.007)	(0.008)	(0.013)	(0.013)
Writing	-0.002	-0.002	0.096	0.102*
	(0.018)	(0.018)	(0.061)	(0.062)
Obs.	7,807	7,807	4,480	4,480
R^2	0.492	0.492	0.671	0.675

Notes: The table presents beauty premium estimates after controlling for height and age requirements. Columns (1) and (3) show results of regressions controlling for height requirement using text-matched samples. Columns (2) and (4) show results of regressions controlling for height and age requirements. Time, job title, and firm size fixed effects are included but not reported. Robust standard errors are shown in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Table A7: Robustness check for beauty premium estimates with minimum salary without adjusting for selection effects

	Female			Male		
	(1)	(2)	(3)	(4)	(5)	(6)
	No matching	Text matching	CEM	No matching	Text matching	CEM
Physical attr./ness	0.035***	0.012*	0.037***	-0.054***	-0.053***	-0.053***
	(0.006)	(0.006)	(0.010)	(0.008)	(0.012)	(0.017)
Vocational training	0.098***	0.154***		-0.039**	0.379***	0.135**
	(0.034)	(0.038)		(0.016)	(0.034)	(0.055)
Associate degree	-0.029***	-0.003	-0.013	0.001	0.026***	0.051**
	(0.008)	(0.008)	(0.017)	(0.005)	(0.008)	(0.025)
University degree	0.047***	0.034***	0.117***	0.148***	0.046**	0.183***
	(0.010)	(0.013)	(0.027)	(0.008)	(0.022)	(0.044)
Other education	0.038	0.020		0.067**	-0.176***	
	(0.035)	(0.083)		(0.027)	(0.055)	
1-2 years	0.082***	0.068***	0.098***	0.039***	0.113***	0.078***
	(0.005)	(0.006)	(0.010)	(0.004)	(0.014)	(0.025)
2-5 years	0.306***	0.293***	0.296***	0.193***	0.194***	0.130***
	(0.008)	(0.014)	(0.024)	(0.006)	(0.018)	(0.035)
5+ years	0.578***	0.801***	0.344	0.443***	0.402***	0.324***
	(0.031)	(0.075)	(0.295)	(0.015)	(0.049)	(0.062)
Non-manager	0.049***	0.020	-0.043	0.005	0.097***	-0.027
	(0.010)	(0.016)	(0.046)	(0.010)	(0.016)	(0.027)
Manager	0.392***	0.291***	0.225**	0.244***	0.333***	0.307***
	(0.020)	(0.032)	(0.088)	(0.014)	(0.047)	(0.071)
Ha Noi	0.025***	0.003	0.032**	0.043***	0.063***	0.028
	(0.005)	(0.008)	(0.013)	(0.005)	(0.009)	(0.020)
HCM	0.078***	0.065***	0.082***	0.047***	0.044***	-0.033**
	(0.005)	(0.008)	(0.012)	(0.004)	(0.009)	(0.016)
Computer	-0.017***	0.017**	0.002	-0.015***	-0.034**	-0.010
	(0.005)	(0.007)	(0.011)	(0.005)	(0.014)	(0.019)
Software	-0.004	0.054***	0.019	0.037***	-0.008	0.030
	(0.007)	(0.014)	(0.017)	(0.006)	(0.016)	(0.026)
Language	0.116***	0.106***	0.070***	0.121***	0.097***	0.130***
	(0.006)	(0.010)	(0.012)	(0.006)	(0.017)	(0.024)
Financial	0.009	-0.055***	-0.062***	0.120***	0.059	0.099*
	(0.006)	(0.008)	(0.013)	(0.009)	(0.039)	(0.052)
People management	-0.018	0.029*	-0.054*	0.098***	0.007	-0.096*
	(0.013)	(0.017)	(0.031)	(0.016)	(0.040)	(0.049)

Table A7: Robustness check for beauty premium estimates with minimum salary without adjusting for selection effects

	Female			Male		
Project management	0.073***	0.051***	0.114***	-0.020***	0.021	0.056*
	(0.010)	(0.017)	(0.026)	(0.007)	(0.028)	(0.031)
Art	0.011	-0.062***	-0.041*	0.026***	0.039*	-0.002
	(0.012)	(0.016)	(0.024)	(0.006)	(0.021)	(0.026)
Character	-0.088***	-0.045***	-0.095***	-0.048***	-0.103***	-0.025
	(0.007)	(0.010)	(0.016)	(0.005)	(0.017)	(0.023)
Cognitive	0.020***	0.023***	0.015	-0.030***	-0.004	-0.025
	(0.005)	(0.008)	(0.012)	(0.005)	(0.015)	(0.021)
Customer service	-0.007	0.042***	0.039***	0.044***	-0.012	-0.024
	(0.006)	(0.008)	(0.013)	(0.006)	(0.019)	(0.023)
Social	0.012**	-0.041***	0.011	0.032***	0.026**	0.024
	(0.005)	(0.007)	(0.011)	(0.004)	(0.011)	(0.018)
Writing	-0.020*	-0.035*	-0.001	0.087***	-0.195***	-0.064
	(0.012)	(0.019)	(0.029)	(0.012)	(0.043)	(0.059)
Obs.	15,027	7,807	3,050	23,905	4,480	1,370
R^2	0.582	0.509	0.472	0.587	0.713	0.670

Notes: The table presents beauty premium estimates for women and men using minimum salary for jobs quoting a salary range. Columns (1) and (4) show results for the whole sample without matching for female and male subsamples, respectively. Columns (2) and (5) show results for text matching for female and male subsamples, respectively. Columns (3) and (6) show results from CEM for female and male subsamples, respectively. Time, job title, and firm size fixed effects are included but not reported. Robust standard errors are shown in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Table A8: Robustness check for beauty premium estimates with maximum salary without adjusting for selection effects

	Female			Male		
	(1)	(2)	(3)	(4)	(5)	(6)
	No matching	Text matching	CEM	No matching	Text matching	CEM
Physical attr./ness	0.062***	0.053***	0.058***	0.024**	-0.000	0.013
	(0.008)	(0.007)	(0.013)	(0.010)	(0.016)	(0.023)
Vocational training	0.198***	0.120*		-0.042***	0.042	0.193***
	(0.045)	(0.065)		(0.014)	(0.031)	(0.064)
Associate degree	-0.024**	0.012	-0.013	-0.011	0.031***	0.080**
	(0.010)	(0.010)	(0.027)	(0.007)	(0.011)	(0.036)
University degree	0.066***	0.057***	0.109***	0.138***	0.026	0.244***
	(0.012)	(0.015)	(0.036)	(0.010)	(0.027)	(0.050)
Other education	-0.003	0.020		0.041	-0.093*	
	(0.042)	(0.139)		(0.032)	(0.052)	
1-2 years	0.074***	0.095***	0.066***	0.039***	0.049***	0.050
	(0.006)	(0.007)	(0.013)	(0.005)	(0.019)	(0.036)
2-5 years	0.285***	0.306***	0.264***	0.179***	0.140***	0.149***
	(0.009)	(0.015)	(0.028)	(0.007)	(0.022)	(0.042)
5-10 years	0.571***	0.768***	0.891	0.423***	0.418***	0.393***
	(0.034)	(0.064)	(0.590)	(0.017)	(0.061)	(0.076)
Non-manager	0.085***	0.099***	0.038	-0.020	0.012	-0.066*
	(0.012)	(0.018)	(0.047)	(0.012)	(0.021)	(0.035)
Manager	0.476***	0.395***	0.357***	0.236***	0.292***	0.264***
	(0.024)	(0.034)	(0.103)	(0.016)	(0.067)	(0.083)
Ha Noi	0.047***	-0.020**	0.034*	0.067***	0.053***	0.040*
	(0.006)	(0.009)	(0.018)	(0.005)	(0.012)	(0.023)
HCM	0.088***	0.048***	0.086***	0.068***	0.024*	-0.035
	(0.006)	(0.009)	(0.018)	(0.005)	(0.013)	(0.021)
Computer	-0.034***	0.010	-0.038***	-0.042***	-0.074***	-0.030
	(0.006)	(0.008)	(0.013)	(0.006)	(0.017)	(0.025)
Software	-0.026***	0.012	0.016	0.049***	-0.021	0.010
	(0.008)	(0.014)	(0.020)	(0.007)	(0.032)	(0.038)
Language	0.117***	0.095***	0.084***	0.119***	0.093***	0.133***
	(0.007)	(0.011)	(0.015)	(0.007)	(0.023)	(0.030)
Financial	0.028***	-0.072***	-0.013	0.154***	0.092*	0.088**
	(0.007)	(0.009)	(0.017)	(0.010)	(0.050)	(0.045)
People management	-0.019	0.053***	-0.044	0.113***	-0.119*	-0.075
	(0.015)	(0.019)	(0.035)	(0.018)	(0.062)	(0.056)

Table A8: Robustness check for beauty premium estimates with maximum salary without adjusting for selection effects

	FEMALE			MALE		
Project management	0.059***	0.066***	0.074***	-0.064***	-0.048	0.028
	(0.011)	(0.016)	(0.025)	(0.008)	(0.033)	(0.036)
Art	0.057***	-0.051***	0.034	0.055***	0.022	0.000
	(0.015)	(0.019)	(0.030)	(0.008)	(0.024)	(0.028)
Character	-0.058***	-0.008	-0.031	-0.048***	0.004	-0.041
	(0.008)	(0.012)	(0.019)	(0.006)	(0.024)	(0.028)
Cognitive	0.025***	0.023**	0.031**	-0.018***	-0.064***	-0.016
	(0.006)	(0.009)	(0.015)	(0.006)	(0.018)	(0.026)
Customer service	-0.001	0.060***	0.036**	0.091***	0.004	0.069**
	(0.007)	(0.010)	(0.017)	(0.008)	(0.022)	(0.027)
Social	0.009	-0.053***	-0.003	0.032***	0.058***	0.020
	(0.006)	(0.008)	(0.014)	(0.005)	(0.015)	(0.023)
Writing	0.007	0.021	0.010	0.093***	0.223***	-0.132**
	(0.012)	(0.019)	(0.029)	(0.016)	(0.080)	(0.061)
Obs	15,027	7,807	3,050	23,905	4,480	1,370
R^2	0.484	0.459	0.353	0.519	0.613	0.604

Notes: The table presents beauty premium estimates for women and men using maximum salary for jobs quoting a wage range. Columns (1) and (4) show results for the whole sample without matching for female and male subsamples, respectively. Columns (2) and (5) show results for text matching for female and male subsamples, respectively. Columns (3) and (6) show results from CEM for female and male subsamples, respectively. Time, job title, and firm size fixed effects are included but not reported. Robust standard errors are shown in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Table A9: CEM balance checks (without adjusting for selection effects)

PANEL A: FEMALE SUBSAMPLE

Multivariate L1 distance before matching: 0.814
Multivariate L1 distance after matching: 0.045
Univariate imbalance

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	L1	**MEAN**	**MIN**	**25%**	**50%**	**75%**	**MAX**
Education	0	0	0	0	0	0	0
Experience	0	0	0	0	0	0	0
Level	0	0	0	0	0	0	0
Location	0	0	0	0	0	0	0
Quarter	0	0	0	0	0	0	0
Job title	0.013	-0.512	0	-5	0	0	2
Firm size	0	0	0	0	0	0	0

PANEL B: MALE SUBSAMPLE

Multivariate L1 distance before matching: 0.918
Multivariate L1 distance after matching: 0.053
Univariate imbalance

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	L1	**MEAN**	**MIN**	**25%**	**50%**	**75%**	**MAX**
Education	0	0	0	0	0	0	0
Experience	0	0	0	0	0	0	0
Level	0	0	0	0	0	0	0
Location	0	0	0	0	0	0	0
Quarter	0	0	0	0	0	0	0
Job title	0.018	0.156	0	0	0	0	0
Firm size	0	0	0	0	0	0	0

Notes: The table reports multivariate and univariate imbalance measures for the female subsample in panel A and makes subsample in Panel B. For both panels, column (1) reports the L1 imbalance measure for each variable. Column (2) reports the difference in the density distributions between treated and control groups at the mean. Columns (3) to (7) report the difference in the density distributions between treated and control groups for the 0^{th} (Min), 25^{th}, 50^{th}, 75^{th} and 100^{th} (Max) percentiles, respectively.

Table A10: Beauty premium estimates for before and during COVID lockdown

	(1)	(2)
	FEMALE	MALE
Physical attractiveness × Pre-lockdown	0.026***	-0.051***
	(0.007)	(0.016)
Physical attractiveness × Lockdown	0.082***	0.051***
	(0.013)	(0.017)
Vocational training	0.130***	0.193***
	(0.049)	(0.031)
Associate degree	0.003	0.017*
	(0.009)	(0.009)
University degree	0.046***	0.007
	(0.014)	(0.023)
Other education	0.014	-0.119**
	(0.108)	(0.053)
1-2 years	0.085***	0.072***
	(0.006)	(0.016)
2-5 years	0.300***	0.166***
	(0.014)	(0.019)
5-10 years	0.778***	0.418***
	(0.066)	(0.051)
Non-manager	0.065***	0.041**
	(0.016)	(0.017)
Manager	0.354***	0.308***
	(0.032)	(0.055)
Ha Noi	-0.013	0.051***
	(0.008)	(0.010)
HCM	0.055***	0.022**
	(0.008)	(0.011)
Computer	0.012*	-0.051***
	(0.007)	(0.014)
Software	0.029**	-0.014
	(0.014)	(0.024)
Language	0.100***	0.097***
	(0.010)	(0.019)
Financial	-0.064***	0.075*
	(0.008)	(0.044)
People management	0.042**	-0.089*
	(0.017)	(0.050)
Project management	0.060***	-0.017
	(0.015)	(0.029)

Table A10: Beauty premium estimates for before and during COVID lockdown

	(1)	(2)
Art	-0.055***	0.027
	(0.017)	(0.021)
Character	-0.024**	-0.034*
	(0.010)	(0.020)
Cognitive	0.021**	-0.042***
	(0.008)	(0.016)
Customer service	0.054***	0.019
	(0.009)	(0.020)
Social	-0.048***	0.039***
	(0.007)	(0.013)
Writing	-0.007	0.096*
	(0.018)	(0.058)
Obs.	7,808	4,482
R^2	0.492	0.674

Notes: The table presents beauty premium estimates for women and men before and during COVID lockdown. Columns (1) and (2) show the beauty effects across subsamples of female- and male-targeted ads, respectively. Skill demand variables and fixed effects are included but not reported. Robust standard errors are shown in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.