Worker Location Preferences and Spatial Inequality: Evidence from a Centralized Assignment Mechanism*

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Abstract

Worker preferences play a fundamental role in shaping spatial inequalities in labor markets and access to public goods. Leveraging administrative data from a large-scale police recruitment in Madhya Pradesh, India, and the theoretical properties of the Deferred Acceptance (DA) mechanism, I estimate police officers' location preferences. Women value proximity to home more than men (12% vs. 7% of base pay). Both prefer areas with better infrastructure, but women also prefer flexible roles and safer locations. Since women constitute a small share of the police force, these preferences produce spatial mismatches under DA, leaving some high-need regions underserved. Estimated preferences imply that a more equitable counterfactual mechanism that preserves the DA mechanism's properties requires only modest compensation, equivalent to 15% of base pay for the average affected officer.

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1 Introduction

Women police reduce reporting barriers for women and lead to lower incidence of crimes against women (Perova and Reynolds (2017), Miller and Segal (2018), Sviatschi and Trako (2024), Amaral et al. (2018), Siwach (2018)). Their presence, therefore, adds to the amenity value of a location, influencing workers' geographical sorting behavior (Diamond and Gaubert (2022)) and, consequently, aggregate spatial inequalities (Diamond (2016)). Given the universal shortage of women police officers, understanding their location preferences is a necessary first step toward addressing these inequalities.

I estimate the location preferences of women police officers and trace their implications for the spatial distribution of women police in the context of Madhya Pradesh (M.P.), a state in Central India with a population of over 72 million (Census, 2011). In India, women police officers are a scarce resource but an essential component of the police human capital stock as they perform tasks that cannot be substituted by their men counterparts. Women constitute only 12.3% of the total police force in M.P. (BPRD (2023)), highlighting the importance of quantifying their location preferences.

To create a thick and competitive labor market for police officers, in 2012, M.P. adopted a centralized mechanism to recruit and match newly recruited police constables to police units using a deferred acceptance (DA) mechanism. Candidates are assigned a police unit, based on their stated preferences, home district, merit rank in an entrance exam, affirmative action policies, and police units' requirements. The matching process is outsourced to a small firm to ensure confidentiality and fairness, and preference lists submitted by the candidates are not shared with the police administration. Leveraging administrative data on location assignments, vacancies, and candidate information with the theoretical properties of the DA mechanism, I identify the location preferences of police officers. Specifically, the stability property of the DA mechanism allows me to convert the two-sided matching problem into a revealed preference problem and estimate preferences using discrete choice models.

Preference estimates reveal a strong distaste for distance from home. Practically all positions require candidates to be assigned outside their home districts, and my results indicate that the average woman candidate would be willing to accept a 12% reduction in base pay to be in a district closest to their home. The corresponding number for men is 7%. Women also prefer flexible positions with fixed hours and routine desk duties, while the evidence is weaker for men. All candidates prefer areas with a better formal economy and better infrastructure as measured by health and education facilities and urbanization levels. Women additionally have a strong preference for areas with fewer reports of sexual assaults, but the same is not true for men. They would be willing to accept a 6% reduction in base pay to go from a district that is at the 95$^{\text{th}}$ percentile to one at the 5$^{\text{th}}$ percentile.

Due to a scarcity of selected women candidates and the non-uniform spatial distribution of their origin districts, the existing matching mechanism leads to inequitable provisioning of women police services across districts. Addressing this is important from a public finance perspective since large districts with a better formal economy are better able to attract women police than small districts, and therefore, they benefit disproportionately from the thicker market for women police created by centralized recruitment. Women police are instrumental in investigating and deterring crimes against women, and the absence of their service is likely to exacerbate existing spatial inequalities in amenities (Glaeser et al. (2001)). Although not explored in this paper, this can also have political consequences (Singh (2019)).

The benefits from an equitable distribution of women police in this context are difficult to quantify. In the context of Madhya Pradesh, Sukhtankar et al. (2022) using an RCT show that introducing women help desks in police stations lowers barriers to justice for women. Amaral et al. (2018) estimates the impact of special women police stations on crime reporting and finds similar results. I find suggestive evidence that the presence and salience of women police lead to more women applicants in the future, and possibly improve women's labor force participation by improving gender norms. Given India's low and stagnant 27% women's labor force participation rate and the influence of gender norms in determining women's work decisions (Jalota and Ho (2024), Heath et al. (2024)), this is an urgent policy area for the country.

To compute the monetary cost of equitable distribution in this setting, I use estimated preferences to simulate outcomes from a counterfactual mechanism that corrects this inequity by accounting for the ex-post shortfall of recruited women. In the counterfactual, the local demand from each police unit that is input into the matching algorithm is adjusted in proportion to the ex-ante demand such that the ratio of women positions left vacant post-matching is uniform across districts. This adjustment creates a welfare loss for selected women officers– the average affected candidate would need to be paid 15% of the basic pay to compensate for the welfare loss. The total annual cost of this counterfactual mechanism is equivalent to hiring approximately 125 additional women officers, merely 10% of the overall shortfall of women police relative to their demand. Furthermore, this alternative mechanism retains all the desirable properties of a DA mechanism, albeit at the cost of added algorithmic complexity.

This paper adds to the literature examining worker preferences and their implications in specific labor market contexts that facilitate the provisioning of essential services while facing unique labor supply shortages. To the best of my knowledge, this is the first paper to estimate location preferences of police in India. Ba et al. (2021) is the only other paper in the literature that investigates police officers' preferences for neighborhood characteristics in Chicago. Boyd et al. (2013) investigates teachers' and schools' preferences for each other. Falcettoni (2018) investigates physicians' location preferences and their consequences for physician shortages in rural areas. My results can inform policy on optimal financial and non-financial incentive structures for public personnel (Dal Bó et al. (2013)). This is an active policy area that is still understudied (see Finan et al. (2015) for a review).[1]

Knowledge about workers' preferences can be used to explain geographical sorting and migration (Black et al. (2014), Diamond (2016), Couture and Handbury (2022), Jia et al. (2023)), gender wage gap (Liu and Su (2024), Le Barbanchon et al. (2021)), job mobility trends (Saks and Wozniak (2011)), structural wage differences (Card et al. (2018), Lavetti and Schmutte (2016), Sorkin (2018)), and the variation in the returns to education and skill (Black et al. (2009)). I add to this work by providing women workers' preferences for job and location attributes. The centralized mechanism in my context has a key advantage, allowing the use of a revealed preference framework similar to Agarwal (2015) and Fack et al. (2019) for better identification of preferences than the existing literature. Even though the setting of my paper is of women police in Madhya Pradesh, my results are consistent with worker preferences in other settings, suggesting their generalizability.

Finally, this paper adds to the growing empirical mechanism design literature highlighting an important limitation of the candidate-proposer-DA mechanism in the context of many-to-one matching when the proposer side of the market is thin. The scarcity of women police leads to the matching mechanism creating a spatial mismatch between women police and the demand for them due to wages being uniform and fixed. Various matching mechanisms exist around the world across markets including education (Abdulkadiroğlu and Sönmez (2003)), kidney transplants (Roth et al. (2004)), armed forces (Sönmez and Switzer (2013)), civil services (Thakur (2021)), and medical residents (Roth (2003)), among others. Economics research on matching mechanisms has motivated a series of policy changes across these contexts (Niederle et al. (2008), Pathak (2017)). This paper is a first step toward understanding and informing policies that promote women's safety and support their broader participation in the economy.

The paper is organized as follows. Section 2.1 describes the institution and the mecha-

[1] The context of centralized police provisioning also draws a parallel with the literature on fiscal federalism (Oates (1999)) as the provisioning of women police is made centrally, whereas benefits of women police are experienced locally.

nism. Sections 2.2 discuss the theoretical properties of the mechanism, which are leveraged for identification. Section 2.3 describes the affirmative action rule and its implications for identification. Section 3 describes evidence highlighting the spatial inefficiency. Section 4 describes the theoretical model used for the identification of preferences. Section 5 describes the data and Section 6 the estimation, parametric identification concerns, and the results. Section 7 discusses the implications of the results and an alternative mechanism and Section 8 concludes.

2 Context

This section explains the institutional rules of police recruitment and unit assignment, which are leveraged for the identification of individual preferences.

2.1 Institution

In 2012, Madhya Pradesh (M.P.), India, adopted a centralized mechanism for recruiting police constables into the state police force. The state conducts an entrance exam testing general knowledge, algebra, and language skills, followed by a physical fitness exam. Qualified candidates are requested to submit a rank-ordered list of their preferences for the different police units in the state. Candidates are not allowed to work in their hometown, except in a few non-public-facing positions. There are 24 armed police units, 23 for men and 1 for women. Therefore, women rank about 60 units, while men rank about 80.

Candidates are matched with police units by a computer algorithm based on their preferences, in order of merit, provided that there's a vacancy in their category.[2] Candidate categories are determined by whether they benefit from any affirmation action policies. By matching candidate preferences with police unit needs, the algorithm simulates the demand and supply sides of the market. The process is outsourced to a small Information Technology firm to ensure fairness and confidentiality of candidates' rank-ordered lists. The number of vacant posts at each police unit is also unknown to the candidates. These features contribute to making the mechanism strategy-proof, i.e., the rank-ordered lists submitted by the candidates likely reflect their actual preferences.

The matching mechanism described above is equivalent to the Gale-Shapley deferred acceptance (DA) algorithm with candidates as proposers.[3] Preference ranking for each

[2] Although it not a requirement, most candidates submit their rank-ordered preference list to the system. In 2016, only 2% of the candidates did not submit their preferences. These candidates are administratively placed.

[3] The mechanism can also be described as a serial dictatorship with merit-based priority within a unit-

candidate is determined at each police unit independently based on candidates' merit, the category-specific vacancy at the unit, and the affirmative action rules in place. The matching algorithm works as follows.

Round 1: All selected candidates apply to their foremost choice of the police unit. Each unit rejects candidates with the lowest priority in excess of the unit's capacity and temporarily holds the remaining candidates.

Round 2: All candidates rejected in the previous round apply to the next best police unit on their rank-ordered list submitted to the system. Each unit pools all applicants together and rejects those with the lowest priorities in excess of capacity while temporarily holding the rest.

Round k>2: Same as *Round 2*.

The algorithm terminates when no rejections are issued. Candidates are matched to the last police unit holding them. Selected candidates undergo training at the police academy and undergo a final medical test before being assigned to a police unit. The initial assignment is fixed for 8-10 years; however, officers can formally request to be transferred to a different unit.[4]

2.2 Properties of the Deferred Acceptance (DA) Mechanism

The DA mechanism is used in many real-world contexts, e.g., schools, colleges, branch allocations in the military, and the medical residency match. The theoretical literature on the properties of matching mechanisms has established that the allocation resulting from a candidate-proposing DA mechanism is not necessarily the best outcome for the other side of the market (Roth (1985)). While the DA mechanism may be desirable in the context of schools and colleges where preferences of institutions are less relevant for policy, its application is unclear in the context of a critical public service such as law enforcement. It is important to understand the extent to which the final distribution of assignments aligns with citizen requirements. My analysis tests this.

The following two desirable properties of the DA mechanism form the basis of my analysis in identifying the location preferences of police officers.

First, Roth (1984) and Roth (1985) show that the DA mechanism in a many-to-one matching context produces a stable match. In my context, stability means that after the final

category pair.

[4]The approval prospects of such requests depend on tenure length, and personnel demand and supply at the time of application.

match, there is no candidate-police unit pair that strictly prefers to match with each other over their given assignments. That is, no candidate can be made better off without making other candidates worse off while also respecting the priorities of the police units. Following Fack et al. (2019), my identification strategy relies on this assumption.[5]

Second, truth-telling by candidates under the candidate-proposing DA mechanism is a weakly dominated strategy (Dubins and Freedman (1981) and Roth (1982)). This means that the rank-ordered lists that the candidates submit are a close reflection of their true preferences. While I don't observe candidates' rank-ordered lists, I observe the preference ranking of the matched police unit. I use this property to test the robustness of my preference estimates and to investigate welfare changes in my counterfactual exercise.[6]

2.3 Affirmative action rule

Government departments in India are required to adhere to affirmative action policies specified in the Constitution and enforced by the Supreme Court of India (see Table 1). There are four vertical reservation categories: Unreserved (General), Schedule Caste (SC), Schedule Tribe (ST), and Other Backward Classes (OBC). Within each vertical category, there are three horizontal categories: Open (or gender-neutral), Women, and Ex-Servicemen. Everybody, regardless of their gender and caste, can be admitted in the unreserved open category based on merit. Reserved categories can only admit candidates of the respective reserved categories.

Sonmez and Yenmez (2019) discusses the possibility of false reporting of preferences and unstable outcomes resulting from the affirmative action policy rule that prevents SC, ST, and OBC women from being assigned under the general women category. A simple example illustrates this. Consider an SC woman with a merit rank of 17 who prefers Unit A over Unit B. Unit A has one vacancy for unreserved women, and the last unreserved woman assigned to Unit A has a merit rank of 25 (worse than 17). However, the SC woman will be assigned to Unit B because she can only compete for SC-designated seats at Unit A, not unreserved women's seats. This leaves Unit A with an empty seat while a more qualified candidate is assigned her second choice, an inefficient outcome inconsistent with the original ideology behind affirmative action.[7]

Strategic false reporting is unlikely to be a concern in this setting due to the nature

[5]I test the sensitivity of my preference estimates to a possible violation of this assumption in Section 6.

[6]In contexts where rank-ordered lists are observed, it is possible to identify preferences based on the assumption of truth-telling; however, Fack et al. (2019) argues that in most empirical contexts, it is more credible to rely on the stability assumption.

[7]The government of M.P. maintains that such inefficiencies would be allowed in the system. Source: http://peb.mp.gov.in/rulebooks/RB_2016/PCT_2016_Rule_Book_Revised.pdf

of incentives for and the timing of caste category revelation. Candidates are required to report their caste category in their initial application to qualify for any benefits associated with reservation, including relaxation in physical requirements, exam score cutoff, and a subsidized application fee. Type-specific unit vacancies are never advertised to candidates, and the size of the market is large enough to inhibit individual strategic behavior.

Moreover, the preference estimates are not affected by this possible inefficiency of DA with the affirmative action policy. I use the exact reservation rules to deduce candidates' eligibility at each police unit-category pair. This allows me to construct personalized sets of feasible police units for each candidate. I use the revealed preference logic to then identify candidate preferences.

3 Descriptive Evidence

The deferred acceptance (DA) mechanism yields optimal assignments for candidates, but realized welfare varies with competition, vacancies, and preferences. A descriptive measure of realized welfare observed in the data is the rank of the assigned unit in each candidate's preference list. 60% of the variation in realized welfare across recruitment rounds is explained by gender, caste, posting type, residence–work distance, and residence and work location fixed effects.[8] This highlights the importance of applicants' residence locations and vacancies in shaping welfare.

Since the DA mechanism prioritizes candidate welfare (Roth and Sotomayor (1992)), the number of selected candidates also becomes a critical determinant of welfare for both candidates and the police units. This is particularly relevant for women due to their scarcity relative to vacancies. Table 2 shows that 90% of women are matched to one of their top five choices, compared to consistently lower shares for men—a direct consequence of weaker competition for women's positions. Since women applicants and selected women candidates are unevenly distributed across the state (see Figures 1 and 2), this scarcity has differential consequences for police units.

The resulting spatial inequity is evident in the proportion of women's vacancies that remain unfilled after assignments (Figure 3). Table 3 shows OLS estimates of the determinants of vacancy ratios.[9] After controlling for the number of vacancies and posting type,

[8] An additional 6 percentage points is explained by merit quantiles within gender and round, and fixed effects for gender and round-specific residence–work matches.

[9] 2016 is the only recruitment round for which vacancy listings were posted by gender and caste. Vacancy information was not available for seven non-civil units including the police training academy, Crime Investigation Department, Telecommunications, and a women-only armed forces unit. Assignments to these units are observed, but determinants of post-assignment vacancies cannot be assessed.

vacancy ratios are lower in districts with stronger amenities and larger nearby applicant pools. By contrast, units in districts with fewer amenities are less likely to attract candidates. Since the presence of women police helps deter crimes against women (Miller and Segal (2018) and Sviatschi and Trako (2024)), this is likely to perpetuate the existing inequality among districts.[10]

Understanding women's location preferences is the first step toward addressing the spatial inequity highlighted above. Preference estimates allow me to quantify the welfare cost of alternative assignment mechanisms. More generally, location preferences provide insights into mobility patterns that can inform internal migration policy (Jia et al. (2023)).

4 Model and Identification

This section discusses the model and assumptions that allow me to transform the two-sided matching problem into a discrete choice problem.

Suppose there are N candidates $i = \{1, 2, ..., N\}$ with types $t \in$ {UR Female, UR Open, OBC Female, OBC Open, SC Female, SC Open, ST Female, ST Open} defined in Table 1, and J police units $j = \{1, 2, ..., J\}$. Suppose that each candidate has a random utility function u_{ij}.

Based on relative values of u_{ij} across j for an individual, he submits a rank-ordered list to the system, denoted by r_i. Each police unit j has type-specific vacancies, denoted by v_{jt} consistent with the affirmative action policy. The mechanism assigns every candidate a priority rank p_{ijt} based on his merit rank and whether he is eligible for assignment under any affirmative action policy. Recall that the mechanism is a candidate-proposing deferred acceptance algorithm where candidates propose to their most preferred units and the units accept proposals in order of priority ranks of each proposer conditionally. In the second step, rejected candidates propose again and units select candidates based on their priority rank from the initial pool of conditionally accepted proposals as well as the new pool. The process continues until all candidates are matched to a unit.

The mechanism produces a match $\mu(u_{ij}, p_{ijt}, v_{jt}) = j$. In equilibrium, cut-offs for priority rank are determined for each police unit. Priority rank is simply the vector of merit rank defined for each candidate category-police unit pair. The cut-off defines the merit rank threshold below which applicants were rejected by the unit. Denote these cut-offs by $C(\mu)$.

[10] There is also suggestive evidence that the presence of women constables and head constables is associated with a greater number of future women applicants, leading to equity in a dynamic sense. Examining the role-model effects of women police is, however, beyond the scope of this paper due to data limitations.

This is a random vector determined by utility shocks ϵ.

The stability of the DA mechanism implies that the candidates are assigned their most preferred available alternative as per the submitted rank-ordered lists. This outcome is the same as that arising from a discrete choice model where each candidate would choose the best possible option from his personalized set of feasible alternatives. Recall that an alternative is feasible if the candidate is eligible for assignment to a particular unit based on the cutoff score of the unit and his priority rank. The set of feasible alternatives can be written as $F(p_{ijt}, C(\mu))$, or F_i for short. It is generally not possible to know the preference relation between the chosen alternative and an alternative for which the candidate was not eligible when relying only on observed matches (Agarwal and Somaini (2019), Fack et al. (2019)). However, in cases where the candidate's assigned unit was first or second in his rank-ordered list, the set of feasible alternatives can be expanded to include all possible units.

Even though in theory the cut-off in any given year will depend on the pool of candidates for that year, the large size of the market and stability imply that cut-offs and individual-specific feasible sets can be treated as exogenous (Fack et al. (2019)).

Utility Function: A police candidate i selects a police unit j located in district d out of the set of feasible alternatives based on their preferences for different amenities available in each location including distance from hometown, and economic and physical infrastructure of each district. I assume a linear additive random utility function u_{ijd}.[11]

$$u_{ijd} = \beta_i * X_{id} + \zeta * K_{jd} + \gamma * Z_d + \nu_j + \epsilon_{ijd} \tag{1}$$

X_{id} represents the distance between the headquarters of police unit j district and the centroid of candidate i's home district. K_{jd} represents the two types of police units based on job flexibility. Z_d represents district amenities reflective of the formal economy, urbanization, health and education infrastructure, crimes against women, and a measure of wages adjusted for housing rent allowance. ν_j represents mean preferences for each police unit. Since most districts have only one police unit, I characterize mean preferences at the district level instead.[12] ϵ_{ijd} is an i.i.d. random utility shock assumed to follow a Type-I extreme value distribution.

β_i denotes individual specific taste for features in distance. ζ represents average preference for a civil unit posting. γ represents average preferences for district amenities that are

[11] Since I am interested in modeling location preferences, u_{ij} is henceforth denoted as u_{ijd}.

[12] In some specifications, I estimate mean preferences for police zones instead of districts to allow for a greater variation in amenities across locations. Empirical concerns are discussed in Section 6.

common across candidates. In the main specification, I model β_i as a function of observable individual traits, denoted by E_i including age, education, marital status, and rural place of origin.

$$\beta_i = \bar{\beta} + E_i * \beta \tag{2}$$

The probability that an individual i is matched with unit j is given by

$$Pr\big(j = \mu(u_{ijd}, p_{ijt}, v_{jt})\big) = argmax_{j \in F_i} u_{ijd} | X_{id}, K_{jd}, Z_d, E_i, F_i; \beta_i, \zeta, \gamma, \nu_j \tag{3}$$

Identification assumptions: Assuming a correct utility function specification, identification of preference parameters relies on the following two assumptions.

1. Given candidate-level observables, preferences and priority indices are independent and no individual can manipulate the cut-offs that determine priority indices. That is, $p \perp \epsilon | X, Z, K, E$.

2. Each candidate's preferences are independent of their own set of feasible alternatives, conditional on observables. That is, $F(p, C(\mu)) \perp \epsilon | X, Z, K, E$.

Since the total number of candidates and vacancies is high and it is not possible for candidates to predict unit-specific vacancies or influence the cut-offs, both of these assumptions are easily satisfied. Each candidate is a very small part of this market. Additionally, a candidate's eligibility is determined by preference lists submitted by candidates with a higher priority order. By assumption, candidates' preferences are independent of each other and therefore, Assumption 2 holds.

The above arguments allow me to transform the matching problem into a discrete choice problem. Similar to Fack et al. (2019), as long as the individual-specific choice sets are exogenous (Assumption 2 above), this transformation is valid. Concerns related to the parametric identification of preferences are discussed in Section 6.

Units differ in their requirements for candidates of different categories and since these are not known in detail to the candidates at the time they submit their rank-ordered list to the system, the set of feasible alternatives can be considered as exogenous even though it is determined in equilibrium. Outside the system, candidates may have additional sources of information but that is an exception rather than the norm and hence, I do not consider that possibility here.

5 Data

To estimate candidates' location preferences, I use administrative data from four recruitment rounds: one in 2012, two in 2013, and one in 2016. The data has information on individual characteristics, the reservation category for which candidates are eligible, the category under which they are assigned, the police unit assigned to each candidate, the rank of this unit in the list of preferences submitted by the candidate, the total number of seats to be filled for each police unit, and the disaggregated vacancy by reservation category for each unit. The rank-ordered lists submitted by candidates is not shared due to confidentiality concerns.

Individual Characteristics: I observe individual characteristics such as home district, sex, and age for each recruitment round. For the 2016 round, I additionally observe education level, whether candidates' residence is classified as rural or urban, marital status, and number of children, if any. The 2016 round also has the largest number of women candidates; therefore, the main analysis uses only 2016 data. The analysis is also restricted to in-state candidates who submitted their preference ranking to the system.[13]

A description of women and men candidates in my estimation samples is in Table 4. Candidates are between 18 and 33 years old, with the median age being 22. 86-93% of women and 54% of men are assigned to civil police units. Most of the remaining men are in the special armed forces, while most of the remaining women are in flexible office-based positions. In the 2016 round, 30% have above high school education, 70-76% are from rural areas, and 3-6% are married. These candidates were assigned to up to 85 police units.[14]

Amenities: Proximity to home has been found to be an important indicator of work location, especially for women (Roback (1982), Boyd et al. (2013), Black et al. (2014), Le Barbanchon et al. (2021), Liu and Su (2024), Barwick et al. (2021)). Therefore, I compute geodetic distances between the centroid of the candidates' home district and the headquarters of the district assigned to them as a measure of proximity to the workplace. Figure 2 shows the location of selected candidates by gender. The average woman is between 124-163 km from her hometown, while the average man is 205 km from his hometown (Table 4).

I also obtain information on various infrastructure amenities, economic activity, and

[13]Residence of out-of-state candidates is not known, so they are dropped from the sample. A negligible proportion of women candidates in each recruitment round are from out of state. Additionally, 98% of all candidates submitted their preferences.

[14]Data on amenities is not available for one of the districts formed after the 2011 Census, when such data was compiled. Therefore, candidates from that district and those assigned to a police unit in that district are excluded from the analysis.

crime at the district level from different sources. District-level literacy rate, sex ratio, population density, the proportion of households with access to water within the household premises, and the proportion of households with TV are from the Census of India, 2011. The numbers of formal establishments and men and women workers working at such establishments are from the Sixth Economic Census 2013-14. Information on the number of schools affiliated with the Central Board of Secondary Education (CBSE) is from a portal maintained by the CBSE. Information on the number of government hospitals and the number of institutional deliveries as a proportion of total deliveries from the District Level Household and Facility Survey 2012-13. Finally, official crime reports are from the National Crime Records Bureau (NCRB) and the state's crime bureau.

Basic pay in this context is fixed across locations by Central Government Regulations. However, there is a cost of living adjustment in the form of house rent allowance determined by urban population levels. I use urban population at the district level from the 2011 Census to construct a variable measure of wages allowing for the house rent allowance adjustment. I use this information to monetize preferences for different amenities and welfare under alternative assignment mechanisms.

6 Estimation and Results

To understand the determinants of women police officers' location choices, I estimate preferences for two broad categories of amenities: those that vary by individuals and police unit locations and those that only vary across police unit locations but are common across individuals. I first estimate the conditional logit model in equation 1 using maximum likelihood estimation for candidates in the 2016 recruitment round separately by gender. Results are in Columns 1-3 of Table 5 for women candidates and Columns 4-6 for men. Data from prior recruitment rounds is later used to assess out-of-sample performance of these preference estimates.[15]

Preferences for Proximity to Hometown: Results indicate that all candidates have a distaste for distance from hometown and women have a stronger distaste for distance than men.[16] A concern with the model in Columns 1 and 4 of Table 5 is the presence of unobserved amenities that are correlated with distance. To allay concerns about endogeneity, I add police-zone intercepts in Columns 2 and 5.[17] Since zone intercepts may not completely

[15]Data for prior recruitment rounds has limited information on candidate characteristics that can be used to account for preference heterogeneity and construct accurate feasible sets.

[16]The comparison between men and women candidates is based on a combined model. Results are not shown here for brevity.

[17]The 50 districts in the estimation sample comprise 11 police zones.

account for unobserved location-specific preferences, I also estimate specifications with district-level intercepts in Columns 3 and 6. This is similar to the first step of the two-step approach of Berry et al. (1995) and Bayer et al. (2007), with the second-step in Table 5. Women's valuation of distance is Rs. 49/km, while men's valuation is Rs.19/km. The average woman candidate would be willing to forego 12% of their basic pay to be in the district closest to their home, and the corresponding number for men is 7%. Results are not included in this draft, but similar valuation results using data from previous recruitment rounds.

The strong distaste for distance from one's hometown reflects the importance of proximity to social networks. Most candidates are between 18 and 25 years of age, with little work or education experience, and most of their social circle is likely in their hometown.[18] Typically, this is their first job after graduating from school or college. About 75% are from rural areas. In this setting, being close to one's family becomes even more important as a social safety for candidates and their families. In a society where women's mobility has traditionally been low, women officers are likely to be even more averse than men to a district assignment far from home. Additionally, since government jobs are highly sought after in this setting and increase one's marriage prospects immensely, being close to home makes the process of 'arranged marriage' easier for candidates' families.[19]

There is evidence of heterogeneity in women's preferences for proximity to their hometown, which is robust across Models 1-3 in Table 5. Women with above-high-school education have a smaller distaste for distance. This could be due to targeting locations not just based on flexibility but the potential for promotion. Women candidates from rural areas also have a stronger distaste for distance. This could be due to limited information about the various police units or reflect the additional mobility constraints for rural residents. The results are somewhat different for men, likely due to differential gender norms and selection into the occupation for men and women.

Preferences for Flexibility: Broadly, there are four different types of units available for new constables: civil police, armed police, railway police, and special branches. Civil police units are the most common type, involving field work and regular interactions with the public in fixed geographical locations. Armed and railway postings entail uncertain duties and locations. Special branches located in major cities include telecommunications, cybercrime, and special investigations.[20] Special branch assignments entail routine office

[18] In the current sample, 90% of the candidates are below 26, with the median age being 22 and 94% of them are unmarried.

[19] Arranged marriage is a common social norm in India, especially in rural areas.

[20] Candidates cannot be posted in their home district, except for two special branches and the women's only armed police unit.

work and predictable hours. They are preferred by candidates desiring flexibility.

Preferences for flexibility are identified from the interaction of flexible posting type and major city indicators, since only the four major cities–Bhopal, Gwalior, Indore, and Jabalpur–employ significant numbers of women officers in both flexible and inflexible units. Results indicate that conditional on being in a major city, women have a strong preference for flexible positions, valued at 14-17% of the base pay. The same is not true for men. Strong negative coefficients on armed and railway postings further highlight aversion to dangerous and unpredictable work.

For women, flexibility likely lowers the cost of balancing professional and household responsibilities, and provide time for exam preparation for higher ranks. Flexibility is thus both a workplace amenity and a pathway to career progression. The results imply that a limited supply of flexible postings can disproportionately affect women's welfare. Consistent with this, He et al. (2021) finds stronger demand for flexible jobs among women workers in China.

Preferences for Economic Infrastructure and Other Amenities: Levels of economic and public infrastructure amenities are often highly positively correlated, making it difficult to credibly identify independent variation to look at substitution patterns between different amenities. For example, districts with greater economic progress and urbanization are also more likely to have a greater proportion of households owning a television or with access to tap water within the household premises, and likely better schools and health facilities as well. Identifying the importance of an individual amenity is also complicated by the possibility of differential levels of information about amenities.

To account for preferences for district-level amenities, I construct a district-level amenity index which is the first principal component of the district-level amenities.[21] Both women and men have a strong and robust preference for district amenities. The value of one standard deviation increase in the amenity index is 5% of base pay for women and 2.5% of base pay for men.

Preferences for Crime: Another district-level amenity that police candidates may care about is crime. Ba et al. (2021) estimates Chicago police officers' preferences for community-level crime and shows that senior officers have a strong distaste for communities with high levels of violent crime, but not so for property crime. In my context, it is difficult to estimate

[21] These include the number of workers employed in the formal sector, an indicator for whether a district has a big hospital, the proportion of births delivered in a health institution, the proportion of households with access to tap water within the premises, the proportion of households with a television, literacy ratio, and the proportion of population classified as urban. Factor loadings indicating the importance of each of these variables in the index are in Table 9.

police officers' preferences for crimes since I only have official data on district-level crime reports and not incidences. Certain crime categories are likely to have less underreporting than others. For example, the level of underreporting in property crimes, murders, and riots is much lower than for rapes or sexual assaults. This is consistent with the evidence found by a victimization survey conducted by an international NGO in a different part of the country (CHRI (2015)). Underreporting of crimes is also likely correlated with district infrastructure and resources.

Additionally, candidates may also be differentially aware of certain crimes from local sources of information or from news reports. For example, candidates may have better information about organized gangs, the general prevalence of crime and gang rapes than about reported dowry deaths, other types of rapes, and specific types of thefts.

Therefore, I only focus on one major category of crimes against women: assaults with the intent to outrage the modesty of women.[22] Assaults are likely easier to report and prosecute, and therefore, may be closer to the true situation than other recorded categories. It is unclear how people form perceptions about this measure but it is likely to be correlated to the reported levels of crimes specific to women. I use the number of assault per 1000 women in a district as a proxy for crimes that women may be especially concerned with.

Women candidates place a significant premium on districts with lower reported assaults against women, while men's preferences are largely unaffected (Columns 1 and 2, Table 5). The value of one standard deviation decrease in sexual assaults is equivalent to 2% of base pay for women.[23] They would be willing to give up 6% of base pay to go from a district that is at the 5$^{\text{th}}$ percentile in terms of safety to the 95$^{\text{th}}$ percentile one, as compared to 17% of base pay to go from a 5$^{\text{th}}$ percentile amenity index district to the 95$^{\text{th}}$ percentile one. This result is consistent with anecdotal evidence that women officers face greater risks of harassment and violence, particularly in understaffed or remote districts.

Robustness of Estimated Preferences: To test the robustness of preference estimates obtained from the 2016 recruitment round, I assess the out-of-sample fit of a model similar to Column 3, Table 5.[24] I use parameter estimates implied by the 2016 recruitment round data

[22]Other important categories are rape and gang rapes. The reported incidence of gang rapes is quite low in the data and the rape reporting is very highly correlated with district-level amenities, suggesting a pattern of systematic underreporting in resource-constrained locations. This is reasonable and important since rape prosecutions require numerous steps to be followed by police officials at the initial stages and especially require women police officers. Lastly, crimes related to domestic violence may be irrelevant for women police officers concerned with their own safety in the workplace.

[23]Results are weaker under the two-step BLP-approach due to limited statistical power.

[24]There are two differences between this specification and the one in Column 3, Table 5: first, age is the only taste-shifter for distance used in this estimation since 2012-13 recruitment rounds do not have information on other individual characteristics and second, indicator variable for special armed forces is dropped since this position was not available in the 2012-13 rounds and so, the variable cannot be defined.

along with individual data from 2012-13 recruitment rounds to obtain predicted shares and compare them with the true shares. Most deviations of predicted shares from the true share are economically small (Figure 4). 90% of the variation in true shares is explained by the out-of-sample predicted shares.[25] Similar to Pathak and Shi (2021), I conclude that parameter estimates from the discrete choice model perform well, suggesting their suitability for policy simulations in this context and beyond.

I also examine the sensitivity of the main estimates to misspecification of feasible sets. I expand the feasible set of candidates identified in Section 4 based on the preference rank of the assigned unit in the individual rank-ordered list submitted to the system. Table 5 already has the most extensive feasible set for candidates who got their topmost choice (50% of candidates). First, I expand the feasible set of candidates who got their second best preference (14% of candidates) to include all options. Most of these candidates have low merit scores and considerably smaller feasible sets. Second, I expand the sets of those who got their second or third best preference (25% of candidates). I estimate the models in Columns 2 and 3 of Table 5 on this altered sample and find a similar pattern of results, although the marginal rate of substitution for distance drops by 13% (see Table **??**).

7 Discussion

7.1 The Appeal of the Deferred Acceptance Mechanism

The centralized recruitment and assignment mechanism was adopted by Madhya Pradesh in 2012 to improve the size of the police labor market and to address concerns regarding corruption in personnel hiring. Prior to that, police zone authorities managed recruitment and assignments in a decentralized manner for small groups of districts, greatly limiting the scope of the market. The choice of deferred acceptance mechanism (DA) was likely motivated by its use in the most prominent education institutions and government jobs in India: the assignment of India's civil servants recruited through the elite Union Public Service Commission exams, the assignment of engineering aspirants to majors, and numerous other college assignments. The DA mechanism rules promote competition by incentivizing aspirants' performance, which arguably improves the quality of candidates.

Other police administrations in India have also adopted centralized recruitment, but without the DA matching mechanism. For example, Uttar Pradesh Police assigns candidates to police units based on distance from their hometowns and vacancies at different units. They do not explicitly consider relative exam scores or candidate preferences in the

[25] A limitation of this comparison is that the demand side is unknown for the 2012-2013 recruitment rounds, so it is possible for the predicted share to be positive even though the actual share is zero.

unit assignment process. This is because police constables are at the most junior level in civil police and the extent to which their entrance exam scores matter for job performance is unclear.

In principle, the DA mechanism offers an improvement over the above mechanism by improving candidate welfare at no extra cost to the police units. However, this is only true if the number of candidates is sufficiently large and police units do not have a preference for candidates' merit scores. When the number of candidates is small relative to the demand for them, the DA mechanism can prove costly for locations that are less attractive as workplaces, as noted in Section 3.

To increase the size of women candidate pool or incentivize assignments to less favorable locations, Madhya Pradesh Police can adopt direct strategies such as information campaigns (Jia et al. (2023)), promotional incentives (Dal Bó et al. (2013)), or training for women applicants to improve selection rates. Alternatively, a small adjustment to the DA algorithm input can be adopted to increase the importance given to police units in the assignment process. I monetize the welfare cost of this adjustment in the following subsection.

7.2 Alternative Mechanism: Vacancy Adjustment for Equity

An alternative mechanism that adjusts the number of unit- and category-specific vacancies based on the number of qualified candidates can help address inequity across police units.

To obtain the adjusted vacancy vector, I first compute the total number of selected candidates eligible for all women's reservation categories.[26] Second, for each unit-category pair, I calculate the ratio of original vacancy to total category-specific vacancy across units. Lastly, I obtain the adjusted unit-category vacancy vector by multiplying the shares from the second step by the number of eligible candidates from the first step.

Theoretically, the DA outcome with this adjusted vacancy vector would lead to equal shares of vacant seats across districts. Empirically, there can be some deviation due to the affirmative action quotas. Nevertheless, the distribution is more equal than the baseline (Figure 5). The outcome is not biased against districts based on their initial amenity levels as observed in Table 3. Since the rules of the mechanism remain unchanged, the desirable properties of the mechanism hold as well.

[26]Only 5 women in the estimation sample were assigned under the Unreserved Open Category; the rest were allocated under women's caste-based categories. Thus, category-specific eligibility is straightforward to compute. Results are robust to ignoring categories and using the total number of selected women.

While women candidates experience a welfare loss, this counterfactual mechanism likely imposes the least possible welfare cost while improving outcomes for the police units and maintaining stability. According to the rural hospital theorem, in the presence of strict preferences, there is no other stable mechanism that is welfare-improving for both candidates and the citizens served by the police units (Roth (1986)). Therefore, any alternative mechanism that improves citizen welfare on account of more police resources will also lower the welfare of police candidates in the absence of a variable wage schedule.

The extensive margin of women's employment decision is likely unaffected by this adjustment to the algorithm. Individual selection into the police force at the constable level suggests the lack of better outside options. Since vacancies are never advertised to candidates, the decision to select into the police force cannot be a function of it. The vacancy adjusted mechanism can lead to more women candidates reneging. However, there is anecdotal evidence that in the current system early quits are being countered by withholding a part of the salary during the probationary period. Since women select into the system with full information about the contract, an adjustment on the extensive margin is unlikely.[27]

I compute the monetary cost of welfare loss to women candidates under this vacancy-adjustment algorithm using preference estimates from Column 2 Table 5. I simulate outcomes under the counterfactual mechanism and compute the expected compensating variation that would make women candidates as well off as under the current mechanism. For a conditional logit model with wages entering the utility function linearly, the exact formula for expected compensating variation is below (Small and Rosen (1981)).

$$\frac{1}{\gamma_w}\Big[ln\big(\sum_{jd} e^{V^1_{ijdz}}\big) - ln\big(\sum_{jd} e^{V^0_{ijdz}}\big)\Big] \tag{4}$$

$$\text{where, } V_{ijdz} = \beta_i * X_{id} + \zeta * K_{jd} + \gamma_w * \text{Wage}_d + \gamma * Z_d + \mu_z$$

V_{ijdz} denotes the indirect utility for candidate i for police unit j in district d and police zone z. The subscripts 0 and 1 indicate baseline and counterfactual scenarios, respectively.

Conditional on being assigned a different police unit, the median candidate experiences a loss valued at 15% of the basic pay of Rs. 26,000 as per the Sixth Pay Commission. Similar estimates are obtained using preferences from Column 3 of Table 5. The total annual cost of compensating all affected candidates is equivalent to hiring 125 additional women officers. The total number of positions left vacant are about ten times this number, suggesting the relative importance of improving allocation vs increasing the number of

[27]Newer recruitment rounds have adopted a more sophisticated preference elicitation interface allowing candidates to choose districts that are not acceptable to them.

selected candidates.

To examine who gets adversely affected in this counterfactual allocation, Tables 7 and 8 compare the preference rank of the assigned unit in candidates' true and simulated rank-ordered lists based on preferences in Columns 2 and 3 of Table 5, respectively. 50% of candidates have the same assignment under both conditions. The distribution of the assigned preference order is less positively skewed under the adjusted rule, highlighting the welfare loss some candidates face. Note that more individuals get their top choice under simulated preferences than in reality (Column 1, Tables 7 and 8 vs Row 4, Table 2). This is due to prediction errors.

Quantifying the benefits of equitable distribution is beyond the scope of this paper, but an equitable distribution is likely to improve the future amenity values of locations through improvements in crime (Sukhtankar et al. (2022), Amaral et al. (2018), Miller and Segal (2018), and Sviatschi and Trako (2024)) and gender norms, and can lead to a more uniform spatial distribution of future applicants. There is suggestive evidence that the presence of women officers encourages more women applicants from the area in the future. The presence of women police constables and head constables in 2014 and the number of women employed in the formal sector explain about 50% of the variation in the location of 2016 women applicants. The presence of 10 women constables or head constables is crudely associated with an increase of 5-10 women applicants in the future from that district. This is likely to have positive spillovers on women's employment in other areas as well by improving location-specific gender norms, which have been shown to be critical for women's labor force participation (Jalota and Ho (2024), Heath et al. (2024)).

8 Conclusion

This paper exploits a novel policy setting to study work location preferences of women. I collect and use administrative data on police candidates in Madhya Pradesh, who are assigned to police units according to the Deferred Acceptance (DA) mechanism based on their rank in an entrance exam and preference lists submitted to the system. The theoretical properties of the mechanism allow me to convert the matching problem into a discrete choice problem, in which candidates select the best alternative from their personalized set of feasible alternatives. This allows me to identify worker preferences for various job and location attributes.

All workers have a strong preference for proximity to home, however, women more so than men. Women's valuation of distance is Rs. 44/km relative to Rs. 27/km for men. All workers prefer areas with a better formal economy and better infrastructure as measured by health and education facilities and urbanization levels. Additionally, women also prefer more flexible job roles and areas with fewer reports of sexual assaults. These preferences are robust across time and are consistent with the larger literature on compensating wage differentials.

Due to the scarcity of women officers, these preferences create a spatial mismatch under the DA mechanism, leading to their disproportionate concentration in districts with better amenities while leaving other areas underserved. This imbalance may exacerbate existing inequalities in law enforcement resources and, consequently, gender disparities in workforce participation. To address this, I propose an alternative assignment mechanism that adjusts vacancy inputs into the algorithm to promote a more equitable distribution of women officers while preserving the desirable properties of the DA mechanism. The estimated welfare loss under this adjustment is relatively small—equivalent to filling only 10% of currently vacant positions—compared to the broader benefits of improved spatial equity. Prior research suggests that a greater presence of women officers not only facilitates crime reporting and reduces the incidence of crimes against women but also enhances women's workforce participation and attracts household in-migration, making this issue particularly relevant within India's social and economic landscape.

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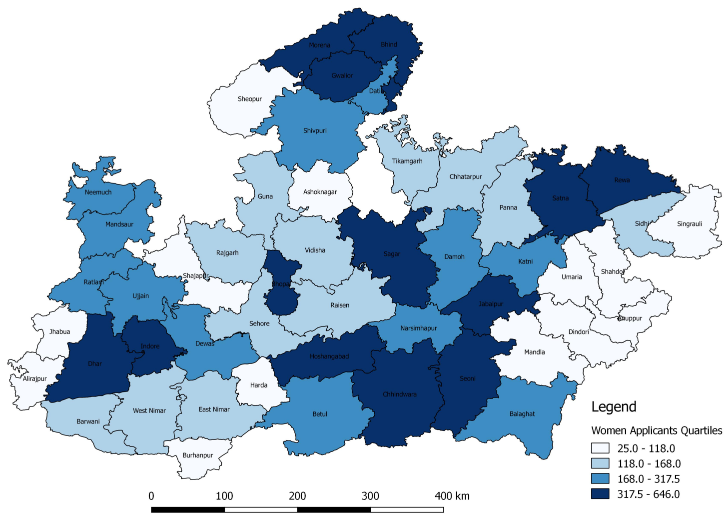
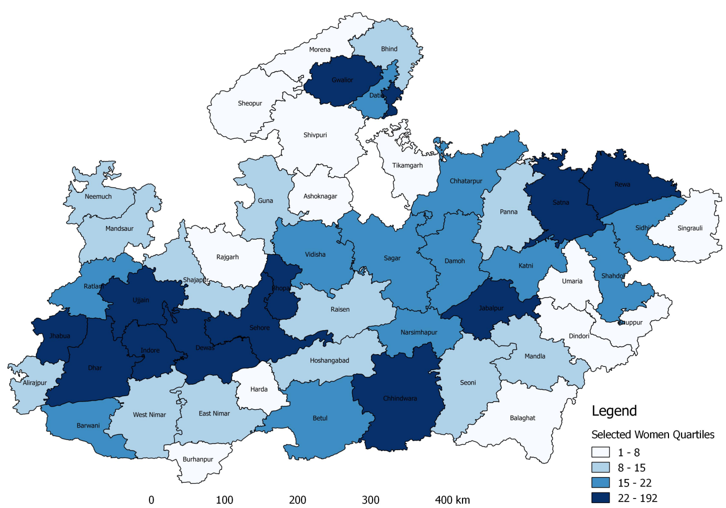
9 Figures and Tables

Figure 1: Spatial Distribution of Women Applicants



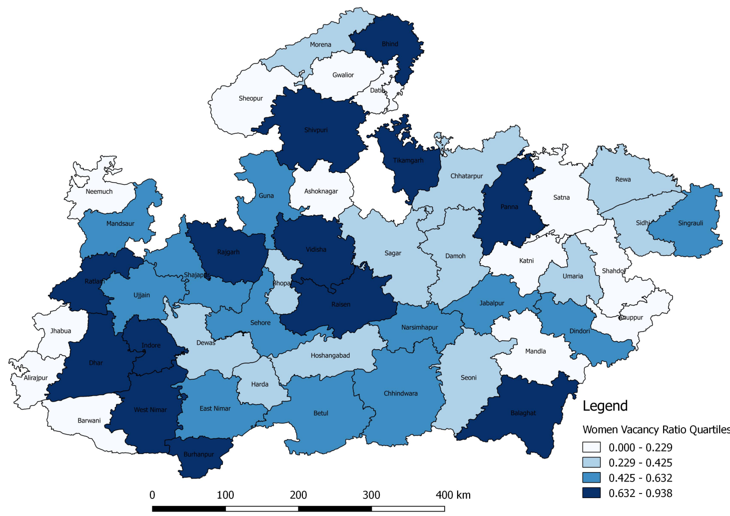
This map shows the districts of Madhya Pradesh with four quartile classes based on the number of women applicants in the 2016 recruitment round from each district. Out-of-state applicants are not included here.

Figure 2: Spatial Distribution of Selected Women Candidates



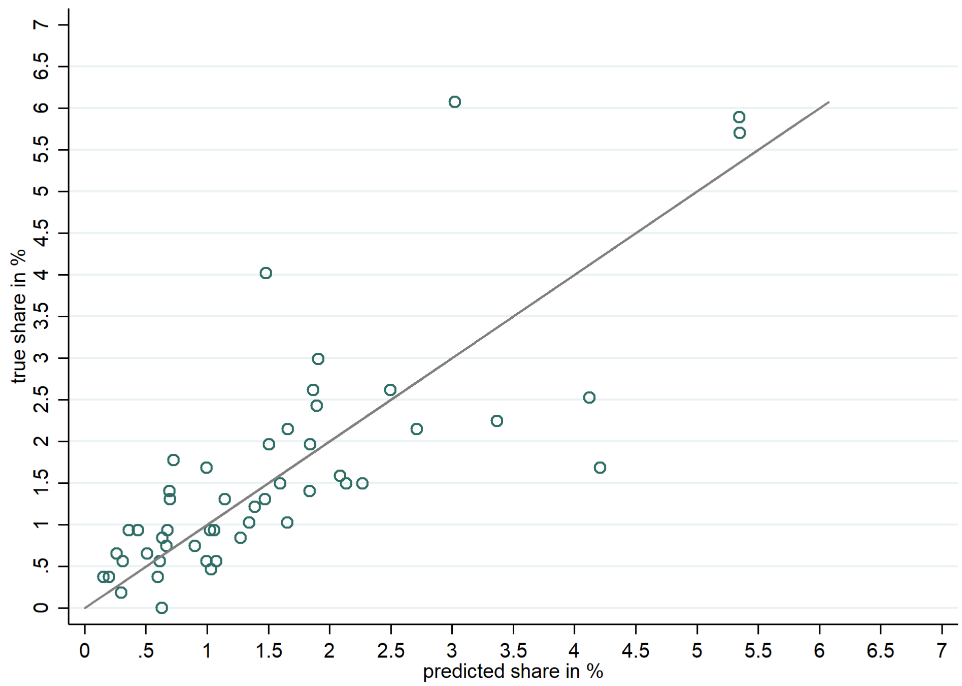
This map shows the districts of Madhya Pradesh with four quartile classes based on the number of selected women candidates in the 2016 recruitment round from each district.

Figure 3: Spatial Distribution of the Proportion of Vacant Women Positions



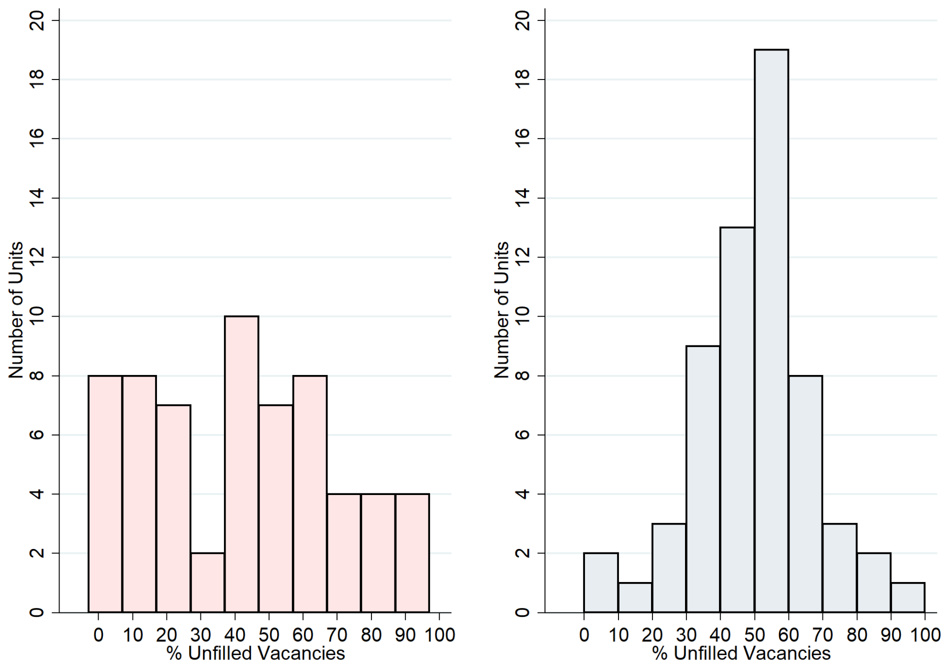
This map shows the districts of Madhya Pradesh with four quartile classes based on the proportion of seats that remain vacant after the assignment. This indicates the extent of unfulfilled demand of each district.

Figure 4: Out-of-sample Predictions



This figure compares the out-of-sample predicted shares at the district level with true shares from a model similar to Column 3 Table 5, but with age as the only individual level taste-shifter since the prediction is for the sample of women recruited in 2012-2013 recruitment rounds. Special armed forces indicator was excluded from the estimation due to no position of such type in the 2012-13 recruitment rounds. Bhopal has been omitted from this graph from readability (predicted share=20.3% and true share=23.4%). R-squared= 0.9

Figure 5: Proportion of Unfilled Vacancies: Baseline vs Counterfactual



This figure shows the distribution of positions for women that are left vacant under the baseline matching mechanism (left) and the counterfactual mechanism (right).

Table 1: Affirmative Action Rules

Vertical reservation	**Horizontal reservation**	**Who is eligible?**
Unreserved Category (UR or General)	Open	Everybody regardless of gender & caste
	UR Female	Only UR Female
	UR Ex-servicemen	Only UR Ex-servicemen
Other Backward Classes (OBC) Category	Open	All OBC candidates regardless of gender
	OBC Female	Only OBC Female
	OBC Ex-servicemen	Only OBC Ex-servicemen
Scheduled Castes (SC) Category	Open	All SC candidates regardless of gender
	SC Female	Only SC Female
	SC Ex-servicemen	Only SC Ex-servicemen
Scheduled Tribes (ST) Category	Open	All ST candidates regardless of gender
	ST Female	Only ST Female
	ST Ex-servicemen	Only ST Ex-servicemen

This Table summarizes the different categories defined by the affirmative action policy (discussed in Section 2.3).

Table 2: Percentage of Candidates Allotted Their Top Ranked Preferences

Recruitment Rounds	Top 1 (in %)		Top 3 (in %)		Top 5 (in %)		No. of Candidates	
	Women	Men	Women	Men	Women	Men	Women	Men
2012	56.52	36.7	94.2	59.82	97.83	70.49	138	3962
2013-I	95.26	24	96.39	40.29	96.39	46.67	443	6458
2013-II	68.95	34.2	78.9	55.44	78.9	65.1	583	4713
2016	50.55	17.03	75.52	30.82	87.01	41.93	1001	8484

This Table shows the percentage of candidates who got assigned one of their top K choices. This is based on observed data on the order of the assigned police unit in the rank-ordered list submitted by the candidates. Rank-ordered lists are not observed.

Table 3: Determinants of Vacancies as a Proportion of Initial Demand of Police Units for Women Constables

	(1)	(2)	(3)	(4)	(5)
Civil Police Unit Indicator	-0.1328	-0.4516**	-0.4974***	-0.6022***	-0.8459***
	(0.156)	(0.184)	(0.180)	(0.216)	(0.222)
Initial Vacancy	0.0052***	0.0078***	0.0080***	0.0091***	0.0103***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Amenity Index		-0.0525**	-0.0592***	-0.0708**	-0.0472
		(0.024)	(0.021)	(0.029)	(0.030)
Assaults per 1000 women			0.7356		
			(0.565)		
Women Applicants within 100km					-0.0021***
					(0.001)
Zone Fixed Effects	No	No	No	Yes	Yes
Observations	55	55	54	55	55
Adjusted R^2	0.24	0.30	0.32	0.23	0.35

Dependent variable is the ratio of vacancy to original postings for women at the level of police units. Type is an indicator variable for civil police units. Out of the 11 other units, initial vacancy was known only for 4 of them. Amenity index represents the first principal component of district level amenities. Factor loadings are in Table 9. Robust std errors are in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Summary Statistics of the Estimation Samples

Variable	Obs	Mean or Proportion	Std. Dev.	Min	Max
Recruitment Round 2016: Women					
Age	994	21.74	2.64	18	32
Above High-school Education	994	0.30	0.46	0	1
Distance in km.	994	123.60	102.74	5	625.37
Rural	994	0.69	0.46	0	1
Married	994	0.03	0.18	0	1
Flexible Posting	994	0.03	0.17	0	1
Recruitment Round 2016: Men					
Age	6,303	22.72	3.13	18	42
Above High-school Education	6,303	0.29	0.45	0	1
Distance in km.	6,303	204.80	163.14	0	802.84
Rural	6,303	0.76	0.42	0	1
Married	6,303	0.06	0.24	0	1
Flexible Posting	6,303	0.03	0.17	0	1
Recruitment Round 2012: Women					
Age	134	22.13	2.86	18	31
Distance in km.	134	145.39	107.70	36.56	476.91
Flexible Posting	134	0.07	0.26	0	1
Recruitment Round 2013 I: Women					
Age	404	23.00	2.76	18	33
Distance in km.	404	126.89	99.90	36.56	625.37
Flexible Posting	404	0.14	0.35	0	1
Recruitment Round 2013 II: Women					
Age	532	22.28	2.65	18	32
Distance in km.	532	162.53	136.62	36.56	788.91
Flexible Posting	532	0.17	0.38	0	1

This Table presents the summary statistics for the estimation samples used for the main model and the robustness checks.

Table 5: Conditional Logit Location Choice Model: Preferences for Distance and Amenities

	(1) Women	(2) Women	(3) Women	(4) Men	(5) Men	(6) Men
Distance in km.	-0.01684***	-0.01889***	-0.02003***	-0.00940***	-0.01120***	-0.01119***
	(0.0009)	(0.0010)	(0.0010)	(0.0003)	(0.0003)	(0.0003)
Above HS×Distance	0.00292**	0.00351***	0.00386***	-0.00152***	-0.00088**	-0.00084**
	(0.0010)	(0.0010)	(0.0010)	(0.0003)	(0.0003)	(0.0003)
Married×Distance	0.00542**	0.00447*	0.00425*	-0.00173**	-0.00141*	-0.00143*
	(0.0019)	(0.0019)	(0.0019)	(0.0006)	(0.0006)	(0.0006)
Rural×Distance	-0.00237*	-0.00212*	-0.00198*	0.00021	0.00124***	0.00125***
	(0.0010)	(0.0010)	(0.0010)	(0.0003)	(0.0003)	(0.0003)
Assaults per 1000 women	-2.71123***	-2.91364**		-0.12187	0.68862	
	(0.7175)	(0.9330)		(0.2659)	(0.3733)	
Index of amenities	0.32436***	0.22781***		0.33616***	0.10775***	
	(0.0429)	(0.0464)		(0.0170)	(0.0196)	
Wage	0.00025	0.00040**		0.00014**	0.00042***	
	(0.0001)	(0.0001)		(0.0001)	(0.0001)	
Main City Dummy	-1.23945***	-1.03110***	-0.14084	-1.52623***	-0.35198**	0.16512
	(0.2565)	(0.2985)	(0.4269)	(0.1028)	(0.1263)	(0.1822)
Flexible Post	-1.82595***	-1.63717***	-1.57136***	-1.74785***	-1.48360***	-1.49985***
	(0.3426)	(0.3488)	(0.3646)	(0.2213)	(0.2253)	(0.2341)
Main City×Flexible Post	2.08708***	1.76175***	1.53731***	0.68432**	0.45527	0.38316
	(0.3723)	(0.3842)	(0.4029)	(0.2366)	(0.2406)	(0.2492)
Armed Forces Post	-2.55082***	-2.59921***	-2.82449***	-5.13019***	-5.18224***	-5.27428***
	(0.4031)	(0.4065)	(0.4141)	(0.0961)	(0.1079)	(0.1094)
Railway Post	-1.35542***	-1.35280***	-1.39393***	-1.04608***	-1.05677***	-1.11862***
	(0.2057)	(0.2076)	(0.2105)	(0.0865)	(0.0871)	(0.0878)
Intercepts	None	Zone	District	None	Zone	District
Individuals	994	994	994	6303	6303	6303
LR chi2	1326.48	1298.81	1362.22	6778.12	6559.30	6845.71
Log likelihood	-2279.69	-2228.20	-2165.26	-15985.41	-15523.18	-15329.65
Average MRS (Rs./km)	67	47	49	67	27	19

The Table presents estimated preferences for the sample of women and men candidates in the 2016 Recruitment Round. There are four types of postings: Civil Police Units (omitted category), Armed Forces, Railways, and Special Branches (Flexible Post dummy). Main city indicator represents Bhopal, Indore, Gwalior, and Jabalpur. Amenity index represents the first principal component of district level amenities. Factor loadings are in Table 9. Std. errors are in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Second stage of BLP for Columns 3 and 6 from Table 5

	(1) Women	(2) Men
Assaults per 1000 women	-0.01544	0.25892
	(2.6134)	(1.0755)
Index of amenities	0.11199	0.00877
	(0.0619)	(0.0198)
Wage	0.00041*	0.00059**
	(0.0002)	(0.0002)
Zone Intercepts (Zone 1 Omitted):		
Zone 2	1.64473***	0.48792***
	(0.1676)	(0.0987)
Zone 3	-0.38350***	-0.92864***
	(0.0742)	(0.0565)
Zone 4	0.49587***	-0.40612***
	(0.1391)	(0.0872)
Zone 5	1.24455***	0.20775*
	(0.2022)	(0.0977)
Zone 6	2.18179***	1.13210***
	(0.0392)	(0.0375)
Zone 7	0.93740***	0.09447
	(0.1391)	(0.0801)
Zone 8	-0.06301	-0.16365***
	(0.0789)	(0.0478)
Zone 9	0.25544	-0.21417
	(0.2979)	(0.1184)
Zone 10	-0.13561	-0.57997***
	(0.2057)	(0.0921)
Zone 11	2.48474***	1.01612***
	(0.0810)	(0.0598)
Adjusted R^2	0.796	0.710
Districts	51	51

Dependent variable is the vector of estimated intercepts from the first stage conditional logit model. Robust std errors clustered at the zone level are in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Percentage of Candidates Allotted Their Top Ranked Preferences Based on Predicted Rank Order from Column 2 Table 5

	Original Vacancy	Adjusted Vacancy
Top 1	58	30
Top 3	88	63
Top 5	97	74
Mean Preference Order	1.7	5

This Table shows the percentage of candidates who will be assigned one of their top K choices by the DA mechanism based on simulated preferences for women candidates in 2016. Original vacancy for women is observed in for all but four units. Predicted rank order is based on a specification similar to Column 2 of Table 5

Table 8: Percentage of Candidates Allotted Their Top Ranked Preferences Based on Predicted Rank Order from Column 3 Table 5

	Original Vacancy	Adjusted Vacancy
Top 1	62	35
Top 3	94	67
Top 5	99	75
Mean Preference Order	1.6	5

This Table shows the percentage of candidates who will be assigned one of their top K choices by the DA mechanism based on simulated preferences for women candidates in 2016. Original vacancy for women is observed in for all but four units. Predicted rank order is based on a specification similar to Column 3 of Table 5

Table 9: Factor Loading for Variables in District Amenities Index

Variable	Factor Loading
log(workers)	0.3265
Big Hospital Dummy	0.3555
Number of CBSE Schools	0.3794
Proportion of Institutional Deliveries	0.2693
Proportion of HHs with Tap Water Access	0.361
Proportion of HHs with a TV	0.4062
Literacy Rate	0.301
Proportion of Urban Population	0.4058

This Table presents factor loadings for the district amenities index variable used in the police unit choice model.