Gender Inclusion in Hiring in India

Learnings from Shortlist: A Market Leader

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EXECUTIVE SUMMARY

In India, there is concern about lost economic growth and development benefits due to low female labor force participation. The low rate seems to be explained in part by challenges in finding appropriate work: a large gender gap in the unemployment rate—particularly among educated, urban women—suggests women face additional challenges finding jobs as compared to men. Evidence has shown that gender diversity in the workplace can have positive effects on productivity and firm performance. While the rise of the internet and online hiring practices can increase access to job opportunities for historically disadvantaged groups, an upsurge in the number of applications can lead managers to intentionally or unintentionally rely more heavily on demographic-based stereotypes. This type of discrimination is a challenge globally, and to counter these tendencies new and innovative tools are needed to reduce bias. We look specifically at the challenge of reducing gender bias in Indian hiring. Using data on hiring for full-time professional jobs in India from Shortlist, a hiring firm that is a leader in using bias-mitigating tools, we consider the validity of the global literature on gender discrimination in the Indian context. We find:

- Strong occupational and industrial segregation by gender
- Gender differences by recruitment channel with a lower percentage of female applicants directly from the Shortlist platform compared to men
- Fewer years of experience among female applicants but higher likelihood of these applicants applying to jobs for which they meet all the minimum selection criteria as compared to male applicants
- Fewer women applying to jobs that include travel or work in rural areas
- Increased likelihood among women to choose to drop out of the pipeline before the application is complete in part due to the need to relocate
- No signs of gender bias in the evaluative stages of the hiring process; once women complete their application, they do as well as men in the process ■

Key Recommendations for Shortlist

1. Use status as a thought-leader to encourage change throughout the sector
2. Think outside the web for new channels to identify female candidates
3. Make it easier for people to create a full account not linked to any specific job
4. Expand use of behavioral nudges to encourage women to apply
5. More intentionally collect operational data

01

Introduction

Improved access to the internet has allowed for wider dissemination of employment opportunities and the chance to use new channels to reach potential talent in hiring processes across the world[1]. Yet, even with increased access to the application process, historically disadvantaged groups may continue to face challenges obtaining jobs due to discrimination and bias in the hiring process[2]. In fact, increasing the number of applicants for jobs could even increase discriminatory behavior because when humans are cognitively overloaded they are more likely to fall back on established heuristics or stereotypes[3]. Therefore, new and innovative tools are needed to accurately screen applicants for relevant competencies to ensure bias does not enter into the hiring process.

Shortlist, a hiring firm based in India, is committed to making the hiring process more efficient and ensuring that the best talent has access to opportunities. Shortlist has created a model that incorporates many best practices to de-bias the hiring process, from relying on competency-based assessments, which have been established by researchers to be the most effective predictors of on-the-job performance[4], to transparency in the number of applicants for each role, which increases the number of female applicants[5]. This has made them a visionary in hiring practices in a country that faces many challenges in reducing discrimination against women and other historically disadvantaged groups. As female economic empowerment and workforce participation is a particularly salient issue in India—the country has a gender equality in economic participation and opportunity rating of 139 countries out of 144[6]—Shortlist has worked hard to create a gender sensitive process. To learn from a leader in the field and to continue to improve our understanding of best practices globally,

[1] Websites that utilize social networks (Facebook, LinkedIn, etc.) are still extremely important in the labor market.

[2] See Appendix A for definitions of key words.

[3] Devine et al., 2002

[4] Schmidt and Hunter, 1998

[5] Gee, 2016

[6] WEF, 2017

we look at gender in the Shortlist hiring process in the context of the specific challenges faced in the Indian market.

Gender inclusion in the hiring process is extremely important as the low rate of female labor force participation is a major barrier to economic growth—India could increase its GDP by 27% if female participation rates matched those of men[7]—and there is evidence that low participation rates are partially a result of discrimination and other barriers in hiring. The female labor force participation rate (FLPR) in India is extremely low at 24% nationally and 16% for the urban population[8], ranking the country one of the lowest at 120 out of 131 countries for which it is measured[9]. Even Indian women who have decided to enter the workforce struggle to obtain gainful employment: there is a large gender gap in involuntary unemployment of 4.7 percentage points (8.7% of working-age women are unemployed but only 4.0% of comparable men are)[10]. This gap is much larger among the highly educated and urban populations at a staggering[11] 8.8 percentage points for both segments[12]. The gender gap in unemployment suggests there are market frictions faced by women that are not faced by men in the hiring process.

When looking at demographic based unemployment or wage gaps, economists attempt to break down the gap into "explained" versus "unexplained" components. The amount of the gap that is due to gendered differences in education, occupational choice, and other observable factors that may determine wages or unemployment is considered "explained." What remains after these factors are accounted for is discrimination. Extensive evidence has established the presence of workforce discrimination globally with regards to hiring, wages, and promotion for women and people of color[13]. For example, in the United States, unexplained factors account for a large share of the gender wage gap; since the late 1980s the unexplained portion has remained relatively consistent, with close to 40% of the gap due to unexplained factors[14].

While discrimination is often hard to identify, there is well-established evidence, particularly in the West, of discrimination in the screening of résumés: studies sending otherwise identical résumés with the name changed to signal different genders or ethnicities found a 50% gap in the call-back rates between white and black sounding names in the United States[15]. Researchers have found consistent results from these types of studies in different contexts and countries, testing different signals

[7] Solberg and Lagarde, 2018

[8] Government of India, 2016

[9] Lahoti and Swaminathan, 2016

[10] These numbers may understate the true number of people willing to work as unemployment numbers do not captured "discouraged" workers (people who have left the workforce and stopped actively looking for work since they were unable to find a job).

[11] In comparison all OECD countries had a gap less than 3.3 percentage points with the exception of Spain, Greece, and Italy which had numbers comparable to India. For example, Mexico's gap is 0.8pp, Turkey 0.01pp, Japan, -0.36 (Azmat et al., 2006)

[12] Government of India, 2016; Raveendran, 2016. In 2015 the urban female unemployment rate was 12.1% while for men it was 3.3% (Government of India, 2016) and among educated women it was 14.6% but 5.8% for the comparable men in 2012 (Raveendran, 2016).

[13] Altonji and Blank, 1999; Olson and Becker, 1983; Bertrand and Duflo, 2017

[14] Blau and Khan, 2016

[15] Bertrand and Mullainathan, 2004

of demographic-based diversity on the résumé[16]. Additionally, work on the Indian gender wage gap estimates that of the ~30.6% gap among educated professionals, a majority is unexplained[17]. In recent years as India has made significant strides in increasing women's educational attainment, reaching gender parity in gross tertiary enrollment[18], the discriminatory component of the gender wage gap has also grown[19]. The documented evidence of gender discrimination in hiring globally and in accounting for wage gaps in India suggests the importance of having hiring processes that attempt to reduce bias and increase gender inclusion.

[16] Bertrand and Duflo, 2016; Azmat and Petrongolo, 2014

[17] Deshpande et al., 2018

[18] UNESCO, 2015; WEF, 2017

[19] Deshpande et al., 2018

Discrimination is also important to address because of evidence that supports the positive effects of gender diversity on both team and firm performance. There is a range of experimental evidence that shows a positive correlation between gender diversity in teams and productivity[20]. In a study that assessed employee satisfaction and team performance in a professional services firm, more gender-diverse offices generated more revenue[21]. Gender diversity has also been shown to have positive impacts on other measures of firm performance, including sales, profits, earnings per-share, and for start-ups the likelihood of market success[22]. These positive effects occur at higher levels of the firm as well: a meta-analysis combining 140 studies on the effect of female board representation on company profitability found a positive effect[23]. This underscores the firm-level business case for gender diversity in hiring and promotion.

[20] Bohnet, 2016

[21] Ellison and Mullin, 2014

[22] Dezso and Ross, 2012; Francouer et al, 2008; Weber and Zulehner, 2010

[23] Bohnet, 2016

Within this context, we use Shortlist hiring data to understand the characteristics of applicants as well as how women perform throughout the pipeline to expand our knowledge of the effectiveness of certain best practices and to assess where there may still be room for improvement. We find that there is a relatively low number of women applying with high levels of occupational segregation, but once women complete their application they do as well as men in the hiring process. This finding confirms global evidence that suggests that women are less confident in the positions for which they apply: they are more likely to meet the minimum requirements for a job and generally apply to fewer positions[24]. Additionally, a higher percentage of applications from men come directly through the

We find that there is a relatively low number of women applying with high levels of occupational segregation, but once women complete their application they do as well as men in the hiring process.

[24] Bohnet, 2016; Ehrlinger and Dunning, 2003; Shipman and Kay, 2014

Shortlist website than from women who are more likely to come through a third-party platform.

From these findings we make five recommendations for how Shortlist can continue to reduce gender bias in hiring:

1. Use position as a thought-leader in this sector to encourage other firms to adopt the practices, including competency-based assessments, that have helped Shortlist create gender sensitive hiring processes
2. Make it easier for people to create a full account not linked to any specific job to build the pipeline of potential candidates
3. Think outside the web for new channels to identify female candidates, particularly in male-dominated industries and occupations and/or in the locations for specific jobs that will not require candidates to relocate
4. Expand use of behavioral nudges to encourage women to apply to additional positions and to complete their applications
5. Improve data collection processes to be able to strengthen feedback loops and organizational learning

Section 2 explains the motivation for this project and background on Shortlist. Section 3 provides information on our overarching analytical framework and data sources. Sections 4–6 look at different steps of the hiring process: early pipeline, recruitment, & evaluation, and assesses where and to what extent bias and discrimination is entering the process. Section 7 suggests potential policy solutions for Shortlist to mitigate the bias in their process and Section 8 concludes and discusses next steps. ■

02

Motivation & Background

Focus on Female Economic Empowerment

As adopted in the United Nation's Declaration of Human Rights, the international community has agreed the right to work is a fundamental human right and through the 2030 Agenda to eliminate gender inequality. However, the case for the economic empowerment of women goes beyond this ethical case; the evidence is strong that it also leads to improved economic outcomes both at a household and country level. One study estimates that $12 trillion dollars could be added to the global economy if countries reached their best-in-region country benchmark in gender parity[25]; increasing female participation to the same rate as men could increase Indian GDP by 27%[26]. At the household level, extensive studies have found that employment and earnings are robust determinants of bargaining power in financial decisions, and when women have more control over financial decisions[27], a higher percentage of household income is spent on investments in children[28]. A strong relationship has also been established between female economic empowerment and developmental outcomes such as children's education, females' age of marriage, and girls' health[29]. In addition to the development gains that happen at a household level, there is evidence that gender diversity at the firm level and inclusive hiring is correlated with higher performance and innovation[30]. Inclusive hiring can also be good for firm level growth as it allows companies to attract and retain the best talent regardless of gender and can better serve consumers in markets or sectors where women are a key customer segment[31]. As discussed in the introduction, gender diversity has also been shown to have positive effects on team performance and productivity and firm performance, including impacts on sales, revenue, and profitability. Reducing

[25] Ellingrud et al., 2015

[26] Solberg and Lagarde, 2018

[27] Qian, 2008; Klasen and Pieters, 2015; Duflo, 2012

[28] WDR, 2012; UN WEE, 2016

[29] Pande, 2017; Qian, 2008; Jensen, 2012; Duflo, 2012; Jayachandran, 2014

[30] UN WEE, 2016; Ellingrud et al., 2015

[31] OECD, 2012

barriers that keep women out of the workforce makes sense for gender equality, macroeconomic growth, firm-level growth, and household well-being, making this an extremely salient issue for India's economic growth and development.

Shortlist, understanding the importance of this issue, actively pursues and supports clients with an inclusive and bias-reducing hiring process. Recently in India, there has been an increased focus on gender diversity in the workforce and many companies are looking to hire qualified female candidates; many Shortlist clients have mentioned this as a hiring goal.

Focus on Educated Women

Gender discrimination in high-skilled jobs[32] is particularly important to understand as the gender gap in unemployment is largest among this population group and the percentage of women with college degrees continues to grow. This is the segment of the population in which Shortlist works: over 90% of jobs for which Shortlist has supported hiring explicitly required a degree. In 2006 enrollment of women in tertiary education was only 9% and by 2017 it had increased to 26.7%[33]. In 1994 only 2.4% of women had tertiary degrees while by 2012 this had risen to 6.2%[34]. Additionally, in the last two decades the FLPR among highly educated, urban (married) women declined from just over 30% to ~25% while comparable male participation stayed constant[35]. This decline comes despite growing returns to education, particularly for graduate education, and there being no evidence that the local supply of high-skilled workers affects FLPR, indicating that the growing population of men with tertiary degrees is not "pushing out" female work[36]. Some of the decline in participation among educated women may be driven by more women obtaining tertiary education for the increasing returns to education in the marriage market with no plans of working.

However, there is strong evidence that the decline is not just explained by the choice not to work but rather highlights other potential challenges for these women in the workforce. 31% of women who primarily engage in domestic duties would like some kind of job; this number rises to over 50% for educated, rural women[37]. The International Labor Office found that from 1994-2010, 38% of the decline in the FLPR was caused by increased education and household consumption levels[38]. However 62%

[32] We define "highly skilled" or "highly educated" as requiring or having at least an undergraduate degree.

[33] WEF, 2006; WEF, 2017

[34] Kapsos et al., 2014: Male enrollment grew although it represented a smaller increase, going from 14% to 27% during the same period female enrollment increased from 9% to 26.7% (WEF, 2006; WEF, 2017).

[35] Klasen and Pieters, 2015

[36] Ibid.

[37] Pande et al., 2016

[38] Increased household consumption levels could reduce FLPR due to the income effect: as households obtain more money, they chose to have the women stop working as it is not necessary for consumption needs. Increased education can lower FLPR because students are not included in the working population so if women who would otherwise be working instead are in school, the FLPR can drop.

(representing a 6.2 percentage point decline in the FLPR) was from diminished employment opportunities[39]. Decreases in opportunity leading to a reduction in the FLPR happens primarily through a discouragement effect where challenges in finding jobs prompt people to leave the workforce. The extent to which the decline in labor force participation of educated women (relative to men) relates to the ability to obtain a job along with the gendered difference in the unemployment rate highlights the importance of better understanding the barriers educated women may face in entering the workforce.

[39] Kapsos et al., 2014: This analysis looks at all working-aged Indians in which they found a 10.1 percentage point drop in FLPR between 2005 and 2010 while male participation dropped by only 3.4 percentage points.

Focus on Hiring Process

The hiring stage is particularly important for reducing labor market inefficiencies as the process typically relies on highly subjective evaluations, increasing the opportunity for discrimination. While discrimination based on gender is illegal under the Indian constitution, in conversations with hiring managers and other labor market experts, all admitted that there is likely some level of gender discrimination in the hiring process across the country—as is the case around the world. A follow up from an Indian government skilling program found that women were 8.58% less likely to receive a job offer despite having identical qualifications and controlling for other factors such as industry[40].

As employment attrition continues to grow as a problem in India, particularly because talent acquisition of skilled labor is

[40] Kapsos et al., 2014: This analysis looks at all working-aged Indians in which they found a 10.1 percentage point drop in FLPR between 2005 and 2010 while male participation dropped by only 3.4 percentage points.

Figure 1 Perceptions of gendered attrition in mainstream media (*The Indian Express 2015*)

becoming more expensive, stereotypes (accurate or not) around the differences in rates of attrition between men and women become increasingly important for their potential for introducing discrimination. A commonly-held stereotype that was mentioned in multiple interviews is that women who are hired directly out of school[41] in their early twenties will leave after a couple of years to have children[42]. As a result, employers are reticent to invest in an employee that they think may leave soon. A study of 22 large multinational corporations sponsored by Shell found that there was a 48% drop in the representation of women between junior and middle levels in India[43]. This drop is much larger and happens earlier compared to other countries where there is large drop later between mid-level and high-level jobs. While this early drop could be due to numerous factors including challenges with promotion, it is often discussed in conjunction with the statistic that at least 75% of women in India leave the workforce at some point in their career because of child care or elder care demands[44]. While the research methodologies and interpretation of these numbers could be discussed, it has fed into Indian mainstream media and the stereotype that women leave in their mid-to-late twenties to have children and have made managers more hesitant to hire women. In India, it is not illegal for employers to ask about a woman's family situation and future family plans in interviews, and employers frequently do so[45]. One experienced HR professional who has worked in talent acquisition at multiple multinational companies (MNCs) in Hyderabad stated that while MNCs typically have policies against asking these questions, it still happens because women are not likely to complain[46].

Additionally, discrimination in hiring may be exacerbated by the Maternity Benefit (Amendment) Bill passed by the government in March 2017, which increased paid maternity leave from 12 weeks to 26 weeks for firms with at least 10 employees. It also requires firms to provide an additional one-year work-from-home option and then child care for the child up to the age of five for any firm over 50 employees. As a result, India has one of the most extensive maternity leave policies in the world. Overall, this policy can help women enter the workforce; however, because the benefits are only mandated for female employees—essentially raising the cost of hiring a woman—there may be backlash to this policy. In other countries, as a result of increased mandated childcare or maternity benefits, there have been documented

[41] In this paper we use the term "school" in the American sense of any full-time educational institution.

[42] Interviews, 2018

[43] Francesco, 2011

[44] Hewlett et al., 2013: This statistic come from a study sponsored by four large multinationals and is produced by a consortium of 80 multinationals.

[45] Interviews, 2018

[46] Interviews, 2018

shifts away from female labor or reduction in women's starting wages[47]. In an online survey of 4,300 Indian startups, SMEs, and entrepreneurs about the 2017 amendment, 40% of respondents said they will still hire women but will "consider if such cost is worth the candidate," while 26% explicitly say they would prefer to hire a man to a woman as a result (22% do not expect it to change hiring decisions and 12% responded that they cannot say the effect)[48]. While the sample may not be representative of firms in India, it does give an indication that in the process of attempting to reduce barriers for women to enter the workforce, there may be a rise in gender discrimination in the hiring process. This increases the importance of ensuring recruitment and hiring systems are designed such that it is harder for discrimination or stereotypes to influence decisions.

[47] Prada et al., 2015; Fernández-Kranz and Rodríguez-Planas, 2013

[48] Local Circles, 2017

Background on Shortlist Hiring Processes

Shortlist provides active support to companies for the hiring process from recruiting and sourcing candidates through shortlisting, allowing clients to use their applicant management platform through the offer and hiring stage. Founded in 2016, they have worked with over 500 companies to hire for positions primarily in India and East Africa. Shortlist positions its competitive advantage on six aspects of their approach: role understanding, scalable screening methodology, objective assessments[49], data beyond the CV to gauge fit and potential, positive applicant experience, and human touch[50]. While some clients choose to work with Shortlist because it is one of the few companies in the market that leverages technology throughout the hiring process for high-skilled professional jobs (from sourcing to shortlisting) with

[49] Shortlist has internally validated its assessments against over 100,000 applicants. Internal validation measures include pass rate analysis, distractor analysis and aiming for a normal distribution on assessment scores. Additionally, external validation has been conducted to correlate job performance scores for hired candidates with their original assessment scores.

[50] Shortlist website, 2018

	Shortlist Clients (India-based Jobs)	Indian Companies
Foreign Involvement	**42%** have at least one non-Indian founder **38%** of companies have operations in multiple countries **28%** of companies have their HQ outside of India	**1.3%** of firms have **10%** or more foreign ownership
Average Company Age	11.8 years	16.6 years

Table 1 Comparison of Shortlist clients to national statistics (*Shortlist data, 2017; Enterprise Survey World Bank, 2014*)

applicant management software, many clients are working with Shortlist because they also believe in Shortlist's goal of reducing bias and structural inequality in the talent acquisition space[51]. Shortlist's client mix includes more people in the latter category than is representative for Indian firms. The clients Shortlist works with are larger, younger, and are more likely to be international companies than the typical Indian firm[52], though over two thirds of Shortlist's clients can be considered "SMEs".

[51] Interviews, 2018

[52] Enterprise Survey World Bank, 2014

Shortlist business operations managers work closely with clients to ensure that their process will effectively match the right person with each role; the pipeline process is as shown in Figure 3. All the steps of the Shortlist process are done through its online hiring platform. While jobs may be posted externally on third-party websites, applicants are directed to the Shortlist platform to apply. Once a candidate has created an application, it becomes easier to apply to multiple jobs as they only need to complete the screening questions and assessments specific to a job.

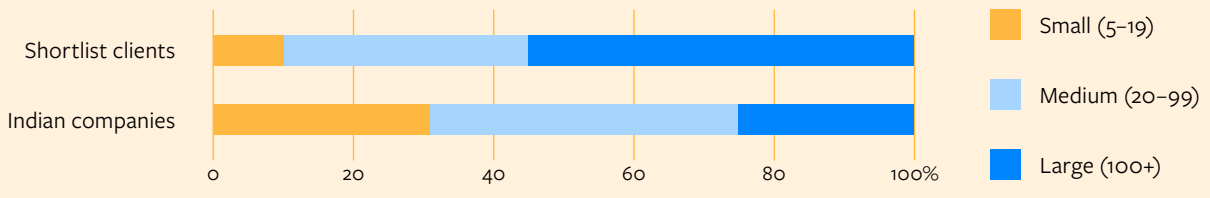
Given Shortlist's goal of reducing bias in hiring, they have already adopted some of the evidence-backed solutions. These include:

- **Structured interviews** in which the same questions are asked to all candidates. Evidence shows this type of interview is better for predicting performance than unstructured ones[53] and reduces space for bias to influence decision making[54].
- **Increasing transparency** with regards to expected salary, number of applicants, and number of people shortlisted. Studies have shown this type of transparency can increase the number of

[53] Schmidt and Hunter, 1998

[54] Dipboye, 1994

Figure 2 Company size, by number of employees (*Shortlist data, 2017; Enterprise Survey World Bank, 2014*)



female applicants as women tend to be more ambiguity-adverse then men[55].

- **Competency based assessments** through which applicants are evaluated on the most important skills for the specific role. Competency-based evaluations are a well-documented way of reducing bias in the hiring process. In a review of the literature, it was found that work sample tests and general cognitive ability assessments were the best predictors of job and training performance of the 19 different techniques evaluated[56]. The assessments allow Shortlist to quickly screen large number of candidates without relying on other commonly-used screening mechanisms such as years of experience which are often not a good indication of on-job performance[57]. Shortlist assessments vary from multiple choice questions based on a reading to a one-minute recording of why the candidate is interested in the role and usually include more than one component.

Currently, approximately 24% of Shortlist applicants are female[58] and close to 32% of job-offers goes to women. These numbers reflect national and industry wide percentages: the overall Indian workforce is 24.5% female, while for firms with at least 10% foreign ownership employees are 33.5% female, and IT companies employ 34% women[59]. Given that the percentage of women offered jobs through Shortlist is higher than national averages and they are already adopting many of the best practices, we can learn a lot from their processes to inform sector-wide techniques for reducing gendered market frictions and increasing female representation in the workforce. ■

[55] Gee, 2016

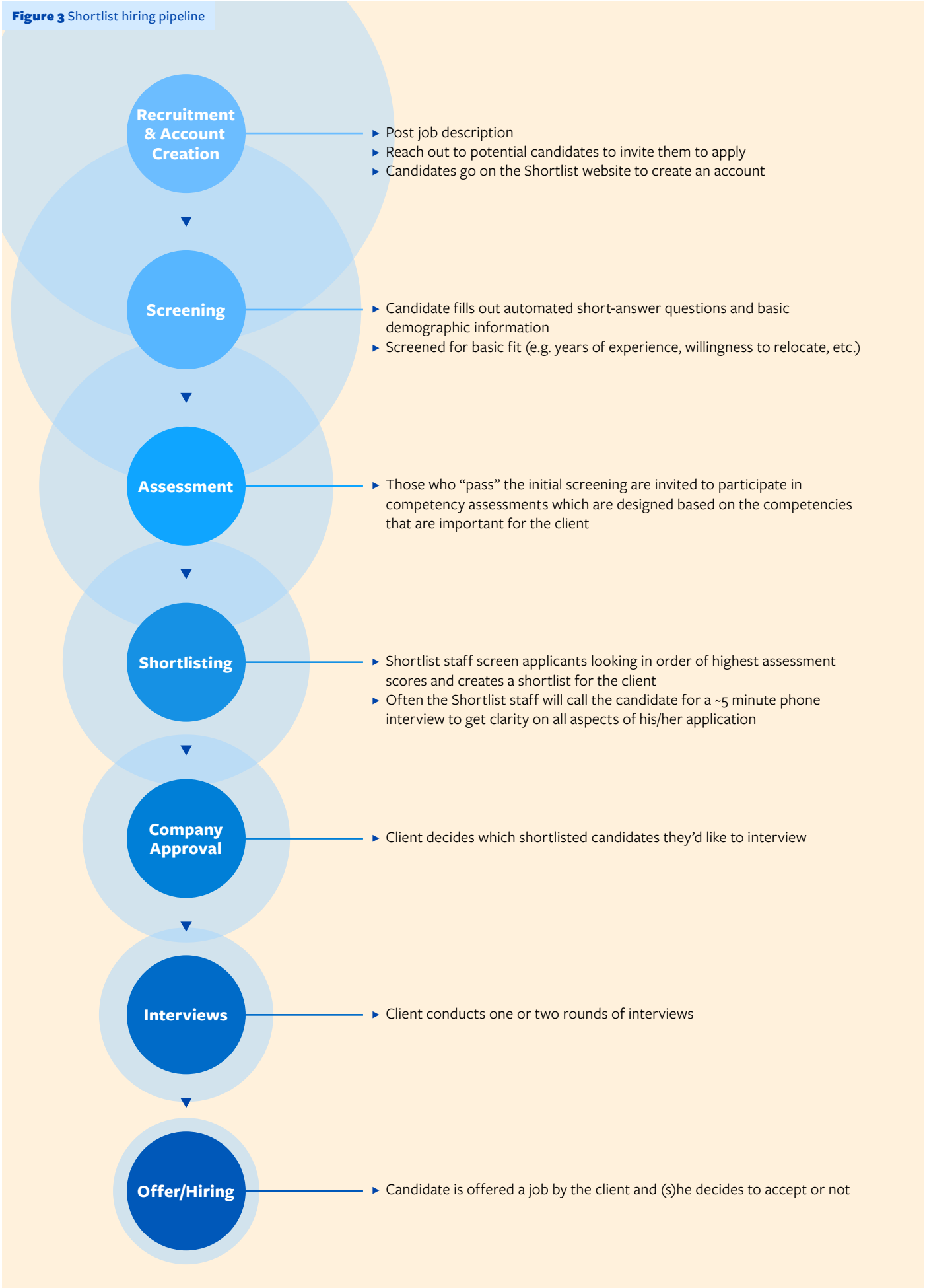
[56] Schmidt and Hunter, 1998

[57] Ibid.

[58] In the next section we go into detail of how we assessed the gender of applicants as Shortlist does not collect gender data.

[59] World Bank, 2017; World Bank, 2014; NASSCOM, 2016

Figure 3 Shortlist hiring pipeline



03

Methodology

Analytical Framework Overview

Since Shortlist has already implemented some of the best practices for bias mitigation, we take a step back and look at all parts of the recruitment and hiring process that could be introducing bias or create gendered barriers informed by global research. We segment the hiring process in three steps (listed in Figure 4) and at each, consider the most likely way that gendered frictions could be introduced. In the following sections, we go into depth about each of these potential issues and how we test the extent to which these may be in the data.

Data Sources

Shortlist Hiring

In 2017, Shortlist provided us data from the close to 200 India-based jobs for which they had hired up to that point; this included 286,991 applications from 211,004 applicants (some people applied to multiple jobs). This data included variables on the applicant, job, and company level (illustrative examples in Table 2). Shortlist provides the opportunity for a candidate to submit a photo (optional) and CV (optional for some jobs) although due to privacy concerns, we did not have access to them.

Shortlist chooses not to collect gender or age data from applicants. However, the Shortlist and client staff may be aware of this information through one of three avenues: gendered name, provided photo, and/or gender and age listed on the CV (common in India). For us to create a gender variable for our analysis we matched first name with lists of baby names[60]. Less than 5% of names did not match using that method; for those, we posted the name on Mechanical Turk and hired Indians to categorize

[60] We used baby name lists found through the US Social Security Administration and open-source datasets using publicly available names scraped from voter lists and other public records in India.

the name as "male," "female," "ambiguous," or "not a name." Combining each method, we created three different gender variables based on different thresholds for gender classification ambiguity (listed in Table 3).

To assess school prestige, we match rankings of universities in India to the university data in Shortlist's database. We created three categories of rank: tier 1, tier 2, and all other. Tier 1 schools included all schools in the top 100 rankings of The Times Higher Education World University Rankings, QS BRICS School Rankings, and The Hindu BusinessLine-MBA Universe Business School Rankings. We also included any school ranked in the top 10% of Ranking Web of Universities from Consejo Superior de Investigaciones Científicas (CSIC) which has 12,000 schools ranked globally. We classify Tier 2 schools as any school found on the CSIC list but not on a top 100 list. We were able to classify and identify 46% of schools on one of these lists. This variable allows us to control for university prestige in the analysis.

For each assessment that Shortlist administered for jobs, we received a description of what skill was tested and a raw score. A typical assessment includes three modules:

1. Skill assessment
2. Voice interview in which an applicant records a 1-2-minute answer to a question typically around their interest in the job
3. A psychometric test (which is not shared with the client and is for the applicant's benefit).

If applicants have already taken a test for another job, they are not required to re-take the assessment. We received assessments data for 182 assessments administered to 14,541 candidates across 113 jobs.

Applicant Level	Job Level	Company Level
First Name	Industry	Age
Years of Experience	Domain (Job Function)	Size
Degree	Job Title	Name
University	Job Description	
Current & Expected Salary[61]		
Competency Assessment Scores		
Status of Application		

[61] Optional for applicants to submit

Table 2
Examples of variables in Shortlist data

Figure 4 Analytical framework

Name	Description	% of applicants' genders classified under this methodology	% of applicants' genders ambiguous under this methodology[62]
Gender 1	Unambiguously male or female; any name that is ambiguous was marked so	9.78%	90.22%
Gender 2	≥60% of occurrences of the name in our name-gender datasets are either male or female, otherwise marked as ambiguous	94.43%	5.57%
Gender 3	>50% of occurrences of the name in our name-gender datasets are either male or female, only "names" in the dataset that were identified as not actually names were marked as ambiguous	98.59%	1.41%

[62] One limitation of our data is that reviewers of applications may be aware of the gender even in cases where we had to code them as ambiguous due to a photo or gender listing on the CV. However, we believe that the gender breakdown of applications marked as "ambiguous" is not statistically significantly different than the classified data with the exception of the offered/hired step due to the small sample size. To account for this, we ran robustness checks including ambiguous names in both the female and male groups.

Table 3 Gender categories

Interviews

To complement the quantitative analysis, we conducted interviews with 9 experts and 5 Shortlist staff in January 2018. The experts included HR professionals, government officials in the labor sector, and civil society leaders working on issues around women in the workforce. In addition to interviewing Shortlist staff on their organizational policy and processes, we shadowed one business operations manager while she screened candidates and made decisions to shortlist or not. Given the small sample size of these interviews, they are not used as the backbone of the analysis but rather provide context and direction to the quantitative work. ■

04

Qualifications & Experience

Every candidate that applies to a job brings years of educational and professional experience; many factors during this early pipeline could be creating gendered differences in hiring. These factors make up the part of the gender gap that is "explained" and could include occupational and degree segregation, differences in university prestige and educational attainment, and discrimination in previous experience, each of which will be explored in more depth below.

Occupational & Degree Segregation

In India, existing occupational and industry segregation is often discussed as a possible negative labor market rigidity[63]. Indeed, the Shortlist data supports these differences in job application by industry. The industry with the highest concentration of female applicants is education (37% female) and public sector (36%)[64] while on the other hand medicine (21%), manufacturing (22%), and renewables & environment (14%) have markedly lower percentages of female applicants[65]. Similarly, there are gender differences with regards to the job occupation ranging from writing, editing, and content jobs (50% female) to engineering (7%) and product management (9%)[66].

Social norms, preferences, and stereotypes are all at play when a woman decides what degree or occupation to pursue. It is worth noting that while this type of segregation exists in India, utilizing a commonly accepted measure of occupational segregation—the Duncan Dissimilarity Index—reveals that India's segregation is relatively low compared to many developed and Latin American countries[67]. Regardless, the segregation could contribute to gendered barriers if there are more employment opportunities

[63] Kapsos et al., 2014; Batra and Reio, 2016; Interviews, 2018

[64] 37% is a (relatively) high concentration of women in the data because overall only approximately 24% of applicants on the Shortlist platform are women.

[65] Government national statistics use different industry classifications, but patterns are similar. For example, in 2010 the share of employees that were female was 42.4% in education but 31.5% in manufacturing (Ghani et al., 2016).

[66] A full breakdown by industry and occupation can be found in Appendix B.

[67] Agrawal, 2016

(or it is generally easier to be hired for) jobs in male dominated industries or occupations.

University Prestige & Educational Achievement Differences

A second way in which the qualification-based gender discrimination could come into play in hiring is if women attend less prestigious universities due to external factors holding "ability" constant. Ability is in quotes because there is evidence that there are no differences in innate ability between men and women[68] and in addition, many assessments of ability may be introducing bias themselves. Stereotype threat[69] can lead to women performing worse on STEM exams or other assessments that are testing skills for which men have traditionally believed to be better[70].

In addition to biased assessments, other factors that could lead to gender bias affecting the enrollment of women in more prestigious university are safety or parental investment in girls' education. Research in New Delhi found that women placed a higher premium on the safety of their commute to colleges than men and chose to attend worse ranked schools that allowed them a safer walk[71]. The study estimated that to improve safety of the route to school by one standard deviation, women were willing to choose a college in the bottom half of the quality distribution over a college in the top quintile (of schools for which they were qualified for based on entrance exam scores)[72] and spend INR 18,800[73] more on tuition than men[74]. Similarly, given that domestic duties typically fall on women, they may choose to forgo prestige of the college or university to be closer to home. Additionally, there is extensive evidence that gender bias has led to underinvestment in girls' education—relative to boys[75]. Despite only looking at highly educated women, gender bias in early investments in education can lead to later stage levels of educational attainment. Investment in education, along with stereotype threat, and external factors such as school location may lead women to differentially attend worse ranked schools or programs than men. As a result, variables such as education which factor into the "explained" portion of gender gaps can be influenced by discrimination earlier in the pipeline.

Of the 30 Indian Universities that are ranked in the top 1,000 world schools in the Times Higher Education 2018 World

[68] Joel, 2015; Johnston, 2005; APA, 2005; Nature Neuroscience, 2005

[69] Stereotype threat refers to the finding that the anxiety of being viewed through a certain lens can lead to cognitive disruption that results in members of a group having a decrease in performance outcomes (Steele and Aronson, 1995; Bertrand and Duflo, 2017).

[70] Spencer et al. 1999; Keller, 2007; Nguyen and Ryan, 2008

[71] Borker, 2017

[72] For the same change in safety, men are only willing to drop from a top quintile college to a top 25 percent college.

[73] This is the equivalent of two times the annual college tuition.

[74] Ibid.

[75] Desai et al., 2010; Azam and Kingdon, 2011

University Rankings, on average 30% of their student body was women; among the 8 Indian Institute of Technology on this list, the average proportion drops to 19%[76]. However, in the Shortlist data, no difference in educational attainment is detected between men and women. To assess differences in school tier by gender, we estimated the likelihood of going to a school in each of the three tiers for each gender. The women in the Shortlist data were in fact more likely to attend a better school; on average, women were 1 percentage point (pp) more likely to attend both a tier 1 and a tier 2 school than men, and 2pp less likely to attend a non-top tier school than men. The direction of this small, but statistically significant difference, indicates that the differential effects of university prestige is likely not affecting women negatively. While it is possible that based on ability, these women could have attended even better schools if not for gendered barriers, these findings do indicate that of the people that choose to apply to jobs through Shortlist, gender differences in educational attainment are not an issue.

[76] Times of Higher Education, 2017

Discrimination in Previous Experience

Like educational qualifications and program prestige, if bias is introduced into the hiring or promotion in a candidates' past employment, it could create differential effects for women and men in the Shortlist data. This effect is apparent in the data on the gender wage gap in India which increases over time, suggesting that there is a "sticky floor" with women struggling to move up the ladder at the same rate as men[77]. While there is limited research that looks specifically at the role of discrimination in promotion in India, there is strong evidence of gender promotion gaps across industries and countries[78]. In Shortlist's data, women have statistically and practically significantly fewer years of experience than men, controlling for job.

[77] Varkkey and Korde, 2013

[78] Bohnet, 2016

Unfortunately, given data limitations, we cannot assess differences in prestige of the current employer or the extent to which the current role prepares someone for the role to which they are applying; additionally, we cannot determine if the lower years of work experience comes from exiting the workforce to have children or from a different mechanism. However, these summary statistics indicate that there are significant differences by gender in past experience, possibly as a result of discrimination.

Recruitment Mechanisms Potential Effects on Educational Decisions and Gender Norms

Companies' concerted effort to increase gender inclusion could have indirect and longer-term effects on some of the early pipeline decisions. A field experiment found that because of targeted recruitment of women for call-center jobs in villages in districts near Delhi, there was an increase in investment in girls' education and a delay in marriage age of the girls as compared to villages that did not receive the recruitment information[79]. This suggests that how firms decide to recruit could affect some gendered social norms and educational decisions.

[79] Jensen, 2012

Early Pipeline Takeaways

While there is little that Shortlist (and employers generally) can do to affect intentional change in the gendered disparities in occupational choice and previous experience that are introduced in the pipeline before candidates apply for roles, these disparities highlight the importance of utilizing the tools within Shortlist's control—recruitment mechanisms and the evaluative processes—to try to reduce gender differences rather than exacerbate early pipeline bias. Additionally, understanding the gendered differences that exist at the start of the process allow us to control for them in the rest of our analysis to not conflate it with bias or discrimination that might be entering later in the process. ■

05

Recruitment & Choice to Apply

Another potential type of segregation that could be introducing gendered labor market frictions is if women self-select into applying for jobs with certain characteristics or recruitment mechanisms. This could contribute to the gender differences in ability to get a job if the self-selection makes these roles more competitive and/or by reducing the pool of jobs for which women are willing to apply reducing their chances of finding a match. Additionally, gender differences in persistence and confidence could be affecting for which jobs women are submitting applications and to how many jobs they choose to apply.

Recruitment Channels & Behavioral Traits

As we found in the early pipeline analysis described above, in the Shortlist sample the women who apply typically are more likely to have gone to a top school although have fewer years of experience. While this can be controlled for in the analysis there are two behavioral traits for which it is more difficult to control for—confidence and persistence—but could end up contributing to gender differences. There is evidence globally that women are not as likely to self-promote and be confident in their ability[80] and as a result are less likely than men to apply to jobs for which they do not meet all the selection criteria[81]. In the Shortlist data, men apply to more jobs; being a woman is associated with 0.4 fewer applications submitted, controlling for school tier, experience level, and the applicant's willingness to relocate. This may be in part because women are slightly more likely to be shortlisted with fewer applications than men. On average, women are shortlisted after applying to 1.48 jobs as compared to men's 1.63

[80] Bohnet, 2016; Ehrlinger and Dunning, 2003

[81] Shipman and Kay, 2014

jobs, controlling for school tier and experience level. This is likely because women are better qualified (beyond the basic controls we included); being a woman in the Shortlist data is associated with a 1pp increase in the percent of the minimum requirements they meet before applying for a job.

Also supporting the global evidence around female persistence and confidence, there is suggestive evidence in the data that women are more likely to start and complete an application if they receive a targeted message rather than finding the job on the Shortlist website and applying directly. 77.21% of female applicants that start an application come through a third-party platform or outreach with the rest finding the job directly on the Shortlist platform. This compares to 76.76% of male applications who come through third party platforms or outreach. These differences are both practically and statistically significant. While we cannot rule out that this difference comes from Shortlist specifically targeting women through their outreach, it does indicate that this type of outreach can be successful at increasing the number of female applicants.

Women seem to be more likely to start and complete an application if they receive a targeted message from Shortlist rather than finding the job on the website, indicating intentional outreach can help increase the number of female applicants.

In addition to explicit online outreach to increase gender diversity, it is useful to also consider how offline recruitment could be used. A survey of 55 IT companies undertaken by NASSCOM found that of hired IT specialists, on-campus recruiting and employee referrals provided the most gender balanced workforce; employees that were identified through these two sources were 50% female. However, staff found through internet advertisement or online job portals were only just over 40% female[82]. Given that all of Shortlist's recruitment is online, we are unable to benchmark it against other recruitment methods and unfortunately there is not additional in-depth research in India or globally about gender differences in recruitment channels.

[82] Raghuram et al., 2017

Job Characteristics & Benefits

Just as the research that found women in Delhi valued the safety of their commute to colleges more than men and chose to attend worse ranked schools that allowed them a safer walk[83], similar effects may be at play with workforce choices. In addition to

[83] Borker, 2017

safety, long hours, inflexible hours, travel for work, "field" based positions, family leave benefits, and the need to relocate for a position are other factors why women may choose not to apply for a role[84]. If women are more selective about to which jobs they apply, this could lead to market frictions not present for men. To understand how these job characteristics and benefits may play into the decision of a woman to apply for a job, we screened the Shortlist job descriptions and coded for the presence of certain words regarding hours, benefits, and travel (see Appendix B for full list). This unfortunately does not assess outside information that may be "common knowledge" about the position or company, and we are unable to assess the safety or proximity of a job to an applicant's home. We find that women are less likely to apply to jobs with the word "travel" and "rural" present in the job description; the presence of the word "travel" corresponds to a 4.7% decrease in female applicants (controlling for all other job characteristics) and "rural" is associated with a 10.7% decrease. We do not find statistically significant differences in applicant rates for any of the other words tested.

[84] Interviews, 2018; UNDP, 2015; Goldin, 2014

Location matters: the presence of the words "travel" and "rural" in a job description leads to a **4.7%** and **10.7%** decrease, respectively, in the number of female applicants & women are less likely to relocate for a job.

Finally, we find that women are much less likely to relocate for a job. In the screening questions, when asked if willing to relocate for the position (which is just asked for those who do not live in the job location), women were 2% more likely to say "no." This of course does not capture the people who have chosen not to apply for the job because of the location which we believe would increase the drop-off from female applicants[85].

[85] While theoretically this difference could arise if men are more likely to self-select out of jobs before the screening process if they know they are not willing to relocate, the qualitative research would suggest that this is not the case.

Our results from analyzing the effect of job characteristics on female applicants confirm the findings in the literature as well as the anecdotal information shared in the expert interviews. The results illuminate the way in which relatively minor shifts in structure of a job can have an impact on the number of female applicants.

Job Description Elements

In addition to the actual characteristics and content of the job, evidence has shown that the way in which the job is described or presented in a posting, and specifically a) the vocabulary used, b)

the elements of the job description, and c) the choices of photo or other visuals have effects on who applies. A seminal study based on a Canadian job board showed that women were more likely to apply to jobs that had more "feminine" words (e.g. "affectionate", "empathetic", "polite") in the description as compared to jobs that had more "masculine" words (e.g. "aggressive", "opinion", "challenge"), controlling for the characteristics of the job itself[86]. Furthermore, evidence has shown that the types of information provided in job descriptions changes the application rate of women. For example, a study on LinkedIn found that if they provided information about how many applicants there were for a position, the number of applications of men and women went up 2–5% but women were 10% more likely to start or complete an application. The authors hypothesized this is due to women being more risk-averse and ambiguity-averse than men[87]. Additionally, seeing diversity reflected in photos on job description pages or company websites also increases the diversity in the applicant pool[88].

Global evidence shows vocabulary used in a job description affects who applies & photos of a diverse workforce on a job description can increase the diversity of the applicant pool.

[86] Gaucher et al., 2011

[87] Gee, 2016

[88] Rivera, 2012

To assess these factors in our Shortlist data, we review the text of the job descriptions for each role, and the way in which the job descriptions were presented. We implemented the methodology developed by Gaucher et al. (2011) to search for and count the appearance of "feminine" and "masculine" words in the text of job descriptions (see Appendix C for full list of words). While we acknowledge that there are potential differences in context between the West and India in terms of what is considered (either consciously or unconsciously) stereotypically feminine or masculine, other evidence has corroborated that gendered stereotypes in the Indian work context are similar to those found in the West[89].

[89] Basu, 2008

Our analysis shows that jobs in the Shortlist data on average had slightly more feminine-coded words than masculine-coded words. This was true across industries, regardless of industry/occupation association. For example, despite being a male-dominated industry, the automotive industry job descriptions on average had more feminine-coded words than masculine-coded words. Additionally, we find no statistically significant difference in application rate of women

Job descriptions posted through Shortlist typically have more feminine-coded words, regardless of industry.

based on the presence of gender-coded words in the Shortlist job descriptions. This analysis indicates that stereotypically gendered words in job descriptions are likely not a primary barrier to entry for female applicants in the Shortlist process.

Recruitment & Choice to Apply Takeaways

Our analysis of the recruitment process and choice to apply confirms gendered differences seen in other contexts of women only applying to jobs for which they meet all the criteria (in contrast to men). The recruitment channel seems to matter, with women more likely to apply if they are reached out to, and there is suggestive evidence that offline recruitment may attract a higher proportion of women than online channels. Additionally, confirming information from the interviews, women are less likely to apply for jobs that include travel, work in rural areas, or would require them to relocate. These findings are important for thinking about potential tweaks Shortlist, and firms more generally, can make in recruiting—explored in more depth in Section 6—to increase gender inclusion. ■

06

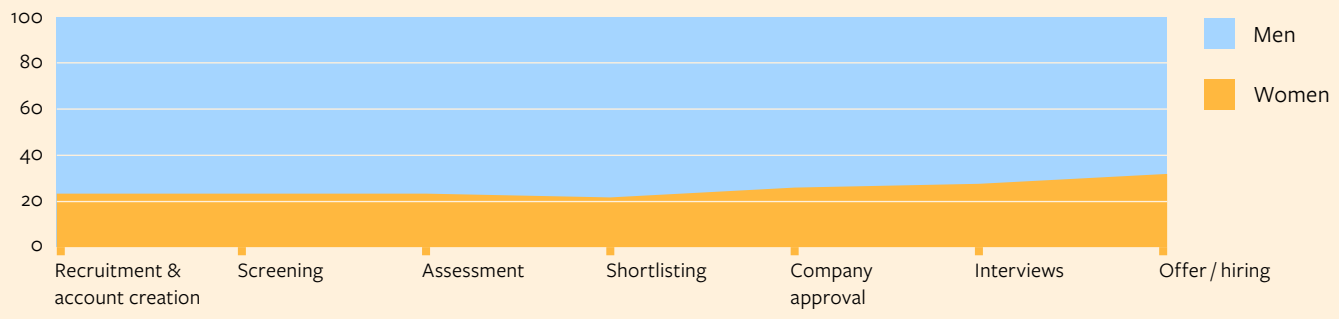
Application Process

The application process itself is the primary way in which Shortlist adds value to clients and provides a mechanism for Shortlist and other firms (either in the recruiting space or in general, through their HR departments) to enact change. To better understand the gender dynamics at play here, we look across the steps of the process to see how woman fare and where they might be dropping out of the pipeline.

Hiring Process Steps

There are a number of ways and stages in which discrimination and bias can present itself in the hiring process even if employers are consciously open to hiring female employees. Traditionally the first step is the résumé screening at which point implicit or explicit bias and stereotypes about women can influence the decision to move a candidate along. At Shortlist the review of the résumé is done in conjunction with reviewing the assessment results and any short answer questions asked during the automated screening process. Bundling this information can help reduce the likelihood

Figure 5 Percentage of applicants to reach each step by gender



to fall back on stereotypes and implicit bias. Typically, after this screening, the next stage in the process—both for Shortlist and other firms—is an interview during which implicit or unconscious bias can be a major factor. The evaluation and decision-making process that occurs post-interview can also introduce bias, with equal performance and competency being perceived and rated differently in for men and women[90].

Given the multi-tiered nature of the hiring process, we wanted to assess where women were most likely to drop out of the pipeline which could indicate the presence of gender bias. When merely looking at the percentage of applicants by gender to reach each step it looks like starting at the shortlisting stage, women do better. However, this does not control for any other characteristics about the applicants or the jobs to which candidates applied so it is impossible to know if these changes are due to explained or observable systematic differences between the female candidates and male ones or due to unexplained reasons[91].

To control for the heterogeneity in applicants' school backgrounds and previous experiences we use a Cox survival analysis framework in which the variable of interest is time until an outcome (e.g. death, marriage, divorce, or in our case, being rejected from the hiring process). Additional details of this methodology can be found in Appendix D. The results of our analysis show ultimately no differences between women

[90] Castilla, 2005; Castilla and Benard, 2010; Monin and Miller, 2001. Here we only look at gender for applicants for whom we were able to classify gender. This assumes that the percentage of ambiguous names that are connected to a male candidate as compared to a female one remains proportional throughout the process. We have no reason to believe that it would change.

[91] Below we look in more depth at the difference between applicants who self-remove (e.g. decide not to complete the application) versus those who are not selected by Shortlist or the company to move to the next round of the process.

	Dependent Variable Pipeline Dropout				
	1	2	3	4	5
Female	1.022** (2.91)	1.016* (2.08)	1.018* (2.29)	0.995 (-0.60)	0.991 (-0.45)
School Tier 2		1.019 (1.55)	1.027* (2.24)	1.022 (1.73)	1.004 (0.12)
School Tier 3		1.006 (0.53)	1.008 (0.73)	1.020 (1.60)	1.016 (0.56)
Minimum Requirements			0.752*** (-22.80)	0.705*** (-23.13)	0.990 (-0.26)
Assessment Mean					0.945*** (-11.18)
N	102,134	93,763	93,763	83,824	14,783
Industry Fixed Effects	No	No	No	Yes	Yes
Occupation Fixed Effects	No	No	No	Yes	Yes

Note:
Significant at the *10%, **5%, and ***1% level. Coefficients represent the hazard ratios: a hazard ratio >1 implies that the variable is positively correlated with dropping out of the hiring pipeline; a hazard ratio <1 implies that the variable is negatively correlated with hiring dropout. Models estimated using a Cox proportional hazard model; standard errors reported in brackets.

Table 4
Summary of Survival Analysis Results

and men's survival rate. There are differences in early pipeline drop out (before the completion of the assessment stage) that are statistically significant with women slightly more likely to drop out even after controlling for school tier and meeting the minimum requirements[92] but this difference disappears when controlling for industry and occupation. Instead, "survival" is driven by meeting the minimum requirements, assessment scores, and (unsurprisingly) self-removal from the process. The results of our analysis for each specification are shown in Table 4.

[92] "Minimum requirements" is a variable that measures the percent of minimum requirements of the job (as listed on the Shortlist job description) that the applicant met, including years of experience and degree type.

Figure 6 Survival rate of women vs men at each stage, excluding fixed effects

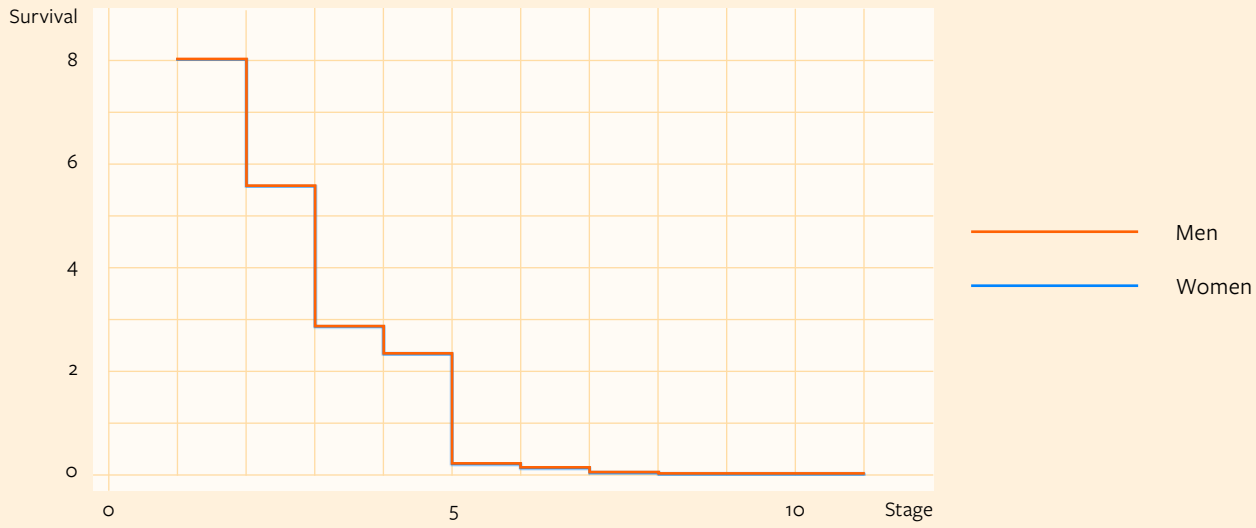


Figure 7 Survival rate of women vs men at each stage, including fixed effects

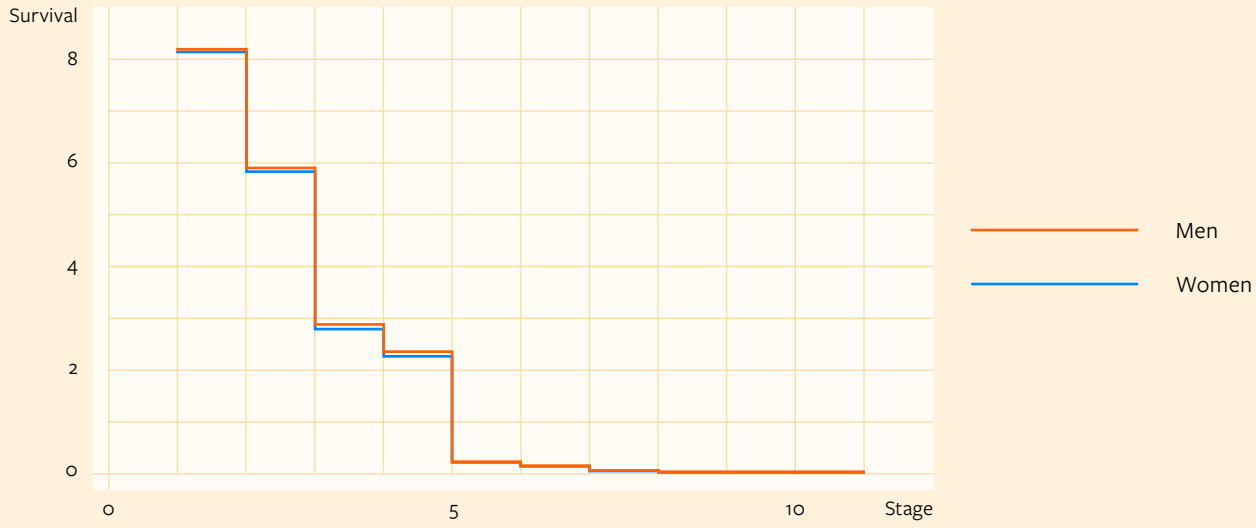


Figure 7 and Figure 6 illustrate the change in survival rate of women as compared to men at each stage. Figure 7 presents the results of specification 3, which does not include industry and occupation fixed effects. In the majority of the first half of the graph, men drop out of each stage at slightly lower rates as compared to women, as evidenced by the red line for men being slightly higher than the blue line for women. However, in Figure 6, which represents specification 4 (including industry and occupation fixed effects), there is no difference between the survival rates.

When we analyze self-removal from the application process[93] we find that women are 3.4pp more likely to remove themselves from the process, controlling for school tier and meeting the minimum requirements. This indicates that a significant portion of women are self-selecting out of the application process (e.g. by not completing the application) rather than being rejected.

We also looked specifically at the competency-based assessments and their role at potentially reducing bias. Due to data limitations we could only do some high-level checks for which we did not find any statistically significant results. The full explanation of this analysis can be found in Appendix D.

[93] The corresponding job statuses for self-removal can be found in Appendix D.

Main Findings

- Strong occupational segregation by gender
- Gender differences by recruitment channel with a lower percentage applicants coming directly through the Shortlist platform for women compared to men
- Female applicants have fewer years of experience but are more likly to only apply to jobs to which they fit all the minimum selection criteria
- Fewer women apply to jobs that include travel or work in rural areas
- Women are more likely to choose to drop out of the pipeline before the application is complete in part due to the need to relocate
- No signs of gender bias in the evaluative stages of the hiring process; once women complete their application, they do well in the process

Application Process Takeaways

From the analysis of the application process it is clear that once women choose to apply, and particularly once they complete their application, they do as well, if not better, than men in the process. ■

07

Policy Recommendations

Given our findings, in this section we look at possible changes that can be implemented by Shortlist and other similar firms to create gender inclusive hiring processes. For each we look at the political supportability[94] and feasibility for implementing changes both internally at Shortlist as well as with regards to their clients and the job applicants.

[94] Here we use the term "political supportability" broadly to include ability to gain buy-in from all relevant stakeholders including Shortlist's clients and the job applicants.

Summary of Policy Recommendations

Sector Involvement

- Use status as a thought-leader to encourage change throughout the sector

Recruitment

- Make it easier for people to create a full account not linked to any specific job
- Think outside the web for new channels to identify female candidates
- Utilize behavioral nudges to encourage women to apply

Application Process

- More intentionally collect operational data

Window of Opportunity for Change

Over the past couple of decades, there has been global pressure to reduce the labor market gender gaps that remain; many MNCs' India offices have created gender targets as they have been set

by their headquarters. In June 2017, Accenture committed to reaching gender parity in their global workforce by 2025 which includes the approximately 150,000 employees they have in India[95]. Over the last few years gender diversity has become a buzzword in India. This reveals shifting social norms—globally and domestically—around the role of women in the workforce. While there are debates about the extent to which the discussion is company marketing versus actual commitment to change, it still provides an opportunity to introduce changes by hiring firms and for Shortlist to continue to advocate for the use of competency-based assessments in hiring.

[95] Kauflin, 2017; Phadnis and John, 2016

At the same time that there has been a growing commitment by MNCs to gender issues, the Government of India has put in place different gender focused initiatives and legislative changes. These include the 2017 Maternity Benefit Amendment, the 2013 Companies Act[96], and Beti Bachao-Beti Padhao[97]. In addition to these changes, in 2017, the Ministry of Human Resource Development mandated that all Indian Institutes of Technology (IIT) give at least 14% of their seats to women[98]. In the interviews, two channels were suggested through which political pressure is being put on the government to make progress on gender issues:

[96] The act requires companies to have at least one female director.

[97] Beti Bachao-Beti Padhao (Save Daughter, Educate Daughter) is a government program intended to prevent gender-biased sex selection and ensure the protection and education of female children.

[98] Bhattacharya, 2018

1. Attempting to attract MNCs to drive growth
2. Trying to increase support among female voters.

Narendra Modi's Bharatiya Janata Party (BJP) party came into power in 2014 on a platform that included both a focus on gender and economic growth. Regardless of the exact mechanisms, the political pressure for gender focused policies and initiatives is illustrative of a growing awareness of and desire to solve gender issues. The gender mandates of MNCs combined with the changing political and social context of India have influenced the client demands on Shortlist with some companies specifically asking for female candidates[99]. This moment in time presents an opportunity for Shortlist to bolster its bias mitigation strategies and encourage clients to see the benefits of its current strategies.

[99] Interviews, 2018

We suggest that Shortlist use its position as a visionary in the field of inclusive hiring to encourage firms to adopt some of its strategies to reduce bias in hiring. Additionally, for Shortlist to continually improve its offering, we suggest thinking creatively about recruitment channels and ensuring that the data systems

are providing relevant and clean information to strengthen feedback loops. While we recognize résumé blinding as a common technique for reducing bias, given the political landscape and potential negative effects (discussed below), we recommend piloting it more extensively before using it widely as a bias mitigation tool.

Sector Involvement Recommendations

Use position as thought-leader to encourage other firms to adopt best practices, including competency-based assessments, that have helped Shortlist create gender sensitive hiring processes. Shortlist, having created a hiring process that incorporates many of the global best practices in which women who apply for jobs do as well as men in obtaining a job, can use its position to lead by example and encourage organizations to incorporate similar strategies (competency-based assessments, transparency, structured interviews, etc.). While these assessments and structures are the backbone of Shortlist's business model, they can be expensive for companies to use relative to traditional methods of hiring. Additionally, given that they represent changes to the status quo and potentially challenges to social norms around gender, it could be difficult to garner enough political will within organizations to create change. But as mentioned, there is a window of opportunity with regards to the political and business landscape for promoting more gender inclusive procedures across all aspects of talent management. Shortlist can use this opportunity along with its experience and results as "proof of concept" to illustrate to other organizations—public and private—the ways in which progress can be made to promote bias-mitigating hiring practices.

Recruitment & Choice to Apply Recommendations

Our findings and global evidence indicate that women are less "confident" in their decisions to apply for a job; the data suggest that women are more likely to apply if they are reached out to. Once women create an account on the Shortlist platform for a job and finish their application, they are likely to do well in the hiring process and there is no indication of systematic gender bias. However, the number of female applicants remains low. This

indicates that in addition to creating a gender inclusive process, an important way for Shortlist and other firms to increase gender diversity in hiring is to think creatively about how to get more women into the pipeline. In the case of Shortlist this means having more women on the Shortlist platform by expanding recruitment channels and then encouraging women to apply for multiple jobs. It is worth mentioning that it is possible that women apply less but are more successful in the process because they are better at identifying jobs for which they would be a good match and therefore increasing the number of female applications without sensitivity to this selection effect could increase the drop-off of women in the pipeline. However, we believe the positive impacts of increasing female applicants would be large enough to offset this possible concern.

Think outside the web for creative and unconventional channels to find people to apply for jobs. Currently many firms, including Shortlist, recruit for jobs solely through online social networks, job boards, websites, and Whatsapp messages. While these represent low-cost tools that can reach a wide audience; given the potential gender bias in online recruiting, we suggest Shortlist and firms more generally strategically identify the occupations and industries that typically have fewer women applying and utilize conventional (career fairs, campus visits) and potentially unconventional offline channels and partnerships to increase the number of women signing up accounts. Additionally, since women are less likely to be willing or able to relocate for a job, we suggest targeting cities for which it posts the most job listings. This recommendation is a bit more challenging, in part due to the concern that using offline networks may reinforce traditional structures of non-gender inequality. Additionally, given India's size to do offline recruiting on a large enough scale for impact would likely take large amounts of resources. It is not clear that this is something clients would be willing to pay for particularly since it is a "public good" in that all companies benefit from this expanded pipeline and therefore there is an incentive for no one company to pay extra for it. As a result, we suggest partnering with local government agencies and civil society organizations associated with industries or occupations to create forum for potential applicants, particularly women, to be exposed to platforms and tools to identify and apply for jobs.

Make it easier for people to create a full account that is not linked to any specific job to strengthen the base of potential applicants that can be encouraged to apply as new jobs are posted. Shortlist is in the early stages of developing and testing "recommendation engines" that help candidates identify other suitable opportunities based on the jobs they already applied for, as well as ways for candidates to apply for specific functional areas rather than specific jobs (e.g. direct sales). We suggest accelerating the deployment of these product features in order to drive greater value for candidates from any individual application instance. We also believe that while this may slightly increase the amount of work that applicants have to do to originally sign-up, the benefits for both Shortlist and the candidate from this additional information will be significant.

Utilize behavioral nudges to encourage women to apply to jobs for which they might be qualified. Shortlist currently uses many behavioral nudges throughout the process including encouraging candidates to finish their applications. These can be used by other firms and more extensively by Shortlist in the process of encouraging women to apply to additional jobs. There is evidence that encouraging women to put themselves up for a position can increase the likelihood of them doing so.[100] Nudges could include messages such as "We saw you applied to X job; people who are qualified for X may be a good fit for Y job." It could also include an explicit acknowledgement that women are less likely to apply for jobs for which they do not fit all the selection criteria than men which is a tactic similar to one that Google is using to increase female self-promotion. Google, noticing that women were less likely to put themselves up for promotions, now includes explicit mention of the data that women are less likely to self-promote and encouraging them to do so in the email announcing the opportunity to indicate interest in a promotion[101]. While this method has not been rigorously evaluated, anecdotes suggest positive impacts from this type of nudge.

[100] Lawless and Fox, 2015

[101] Bohnet, 2016; Kang, 2014

Nudges can also include ensuring that an equal employment opportunity (EEO) statement is included in all job descriptions; there is evidence that inclusion of an EEO statement increase the attractiveness of the organization to women[102]. Given the gendered differences we see in the likelihood of someone starting and completing an application depending on the source of the outreach, we think that by making small changes in how and when

[102] Avery and McKay, 2006

women are encouraged to apply for additional jobs can be a simple way to marginally increase the number of female applicants.

Application Process Recommendations

Our analysis indicates that application process is working well in reducing potential gender bias however there may be a slight discouragement effect for women with more women choosing to not to finish their applications. Therefore, we recommend the following:

More intentionally collect operational data to strengthen feedback loops. While not asking for gender in the application process sends a strong signal to candidates that gender is not a factor in hiring, the reality is through names, résumé information, and recorded audio, the gender of applicants will almost always be known. Shortlist not having gender information (or other demographic data such as age) means that it is hard to measure potential problems and test new solutions to improve diversity and inclusion. While administratively it would be easy add an optional question on gender, it might be more challenge politically in that in some countries it is illegal to ask about gender and many clients may feel uncomfortable having it asked. Two possible ways to try to implement this that may be more politically sensitive to potential client concerns are:

1. Use scraping and/or natural language process techniques to pull the gender that may be listed on the résumés. This is politically more supportable because it will merely better collect the information voluntarily provided by candidates. However, it may be more administratively challenging to implement and will only pick up gender for those that include it on the résumés.
2. Separately from any specific application, encourage applicants to fill out an optional profile that clearly states that the information provided will not be shared with anyone screening the applications and is rather used for internal product improvement (like the messages asking if you want to send a "crash" diagnostic information to Microsoft or Apple).

Collecting gender data and possibly additional demographic information including age can help Shortlist in the future tailor their products and processes to reduce biases and increase

inclusion. It can also allow Shortlist to test elements of the assessments to see if the reason women are less likely to finish them can be identified and test new assessments to ensure that gendered characteristics (not directly being tested by the assessment) such as risk and ambiguity aversion are not creating gender gaps in scores.

It is worth noting that while résumé blinding is often promoted as a tool for reducing gender bias, for Shortlist and other firms that are already sensitive to gender inclusion, we do not recommend this as a top recommendation. Multiple studies on résumé blinding (removing gender- and/or race- or ethnicity-identifying information) have shown that this can help control for implicit bias[103]. Important in the literature on blinding is the evidence that finds for firms that are intentionally trying to hire from traditionally disadvantaged groups, blinding can have an adverse effect[104]. Given Shortlist's intentionality towards creating a bias-free process and that we do not find evidence of gender discrimination in the Shortlist process, we believe that it is possible that blinding in the Shortlist process could have an adverse impact on gender inclusion. Additionally, there is evidence that among many companies there is a lack of interest or support for blinding[105]. However, we suggest some simple tests for Shortlist and other companies to utilize to understand the way in which blinding of certain elements could impact hiring decisions: have all the hiring managers screen the same set of applicants randomizing which applicants are blinded for different managers and compare the final shortlists. Because of the potential negative impact, combined with the fact that there has been lack of political support for adoption, we do not recommend blinding as a key tool to increase gender inclusion[106]. ■

[103] Bertrand and Mullainathan, 2003; Åslund and Skans, 2012

[104] Behaghel et al., 2015

[105] Interviews, 2018

[106] It is important to note that we only looked at gender and so cannot conclude the effectiveness of blinding for reducing potential other demographic-based bias.

08

Conclusion

To understand how Indian firms can increase gender inclusion in their hiring processes, we looked at the gender dynamics at play in the context of a firm utilizing many of the best bias-reducing practices at three stages of the hiring process: early pipeline characteristics, recruitment and choice to apply, and the application process. We find that high levels of gendered occupational segregation and women who apply to jobs through Shortlist are more likely to have strong academic qualifications but fewer years of experience than male candidates. Additionally, there is generally low participation of women with just 24% of applications coming from women, reflecting national social norms. While there is little Shortlist and other firms can do to shift the social norms and stereotypes that lead to gender disparities in experience and occupational segregation, these findings can help influence their recruitment strategy. Through our analysis of the application process, we find that once women are in the pipeline, particularly after they finish their application, they do as well as men. We do find that women are slightly more likely to drop out or remove themselves during the early steps of the application—in large part due to the need to relocate.

These findings are encouraging as they suggest that the findings of best practices in other countries are applicable to the Indian market. From our analysis, we recommend that Shortlist continue to utilize the competency-based assessments, transparency, de-gendered language in job descriptions, and structured interviews while encouraging other firms to adopt similar practices. Since it is promising that women do well once they are in the pipeline, to further gender inclusion, Shortlist can focus on building the pipeline of potential applicants especially looking to unconventional channels in traditionally male-dominated

fields to utilize encouragement and behavioral nudges to increase the number of relevant female applications to any given job. We also recommend that gender information is more systematically collected in order to strengthen its learning feedback loop and continue to improve its processes.

There were some limitations to this analysis; for example, due to the lack of surnames in our data, we were not able to try to code the caste or religion of the applicant. There is evidence from an experiment on résumé screening for a New Delhi call-center that there was bias for upper-caste names[107]. Despite these data limitations and Shortlist not being representative of firms in India, we believe that all organizations can learn from Shortlist's processes that create an effective system for reducing bias in hiring. Reducing bias and increasing gender inclusion can decrease the gendered frictions that play a role in India's gender unemployment gap and low FLPR. Increasing FLPR is particularly important because the country would be able to reap additional economic and developmental benefits if more women entered the workforce.

[107] Banerjee et al., 2009

While increasing gender representation and inclusion in the hiring process is extremely important for building the pipeline of talent in companies across the country, these initiatives will only be fully successful if they go together with other diversity and inclusion efforts. Firms must do additional work to ensure there are no gender differences in other human resource policies including compensation, promotion, and leave. Importantly, firms will only enjoy the benefits of increased diversity if management and colleagues include women and other members of diversity groups as active participants with their voices heard, respected, and valued to ensure a sense of belonging for all employees. ■

Opportunities for Further Research

Building on these findings, we recommend additional research be conducted to provide employers and policy makers with practical guidance on how to achieve gender inclusion in the workplace through enhanced hiring practices. Critical future research questions could include:

- Do these findings apply in other emerging markets, such as East Africa?
- How do you attract and hire women who are seeking to re-enter the workforce after family leave?
- Which organizations have created a gender diverse workforce across seniority levels and what have they done to achieve this?

09

Appendices

Appendix A

Key Word Definitions

- **Stereotypes:** The academic literature breaks stereotypes—or widely held generalizations or beliefs about groups—into two categories: statistical and biased.
  - **Statistical stereotypes** arise from "...rational formation of beliefs about a group member in terms of the aggregate distribution of group traits" (e.g. "U.S. elementary school teachers are female,"; 87% are).
  - **Biased stereotypes** are ones based in widely held but wrong beliefs about groups. They often amplify or exaggerate a difference that is low-probability but representative of a group (e.g. "Irish are red-headed;" only 10% are)[109].
- **Discrimination:** When these stereotypes lead to difference in treatment of a member of a minority group as compared to an otherwise identical member of a majority group is discrimination[110]. In addition to belief-based discrimination, discrimination can also be taste-based. This latter type of discrimination is based on personal preference or prejudices about a group unrelated to any stereotype.
- **Bias:** The term bias is broad, encompasses discriminatory behavior or merely attitudes based on assumptions, stereotypes, and prejudice, and can be explicit (i.e. a clearly stated preference for one gender) or implicit (i.e. unconsciously affecting choices and actions).
- **In-group preference or bias:** People typically prefer hiring others that hold similar beliefs, personality traits, and or attitudes but given those characteristics are often hard to discern in other individuals, visible traits and demographic features are used as a proxy[111]. This

[109] Bordalo et al., 2016; Coffman et al., 2017

[110] Bertrand and Duflo, 2017

[111] Gonzalez and DiNisi, 2009; Uotila, 2017

preference for people who are within the same group as yourself is in-group bias.

- **Segregation:** In this paper we use segregation to refer to a state in which members of one demographic group are disproportionately present in an occupational or educational group. The gender segregation found in the workforce in India (described in more detail below) is a result of both self-segregation as well as segregation imposed or created by others. Even self-segregation can arise because of stereotypes, with stereotype threat being a well-documented factor in women's educational and occupational decisions[112]. While occupational and educational segregation can be a result of stereotypes and bias through explicit channels as well as more implicit ones, they can also arise from mere variances in preferences. Unfortunately, it is difficult to disaggregate the different mechanisms at work.

[112] Ramaci et al., 2017; Steele et al., 2002; Gupta and Bhawe, 2007

Appendix B

Variable	Women	Men	Significant Difference ($p < 0.05$)
Total Experience (Years)	5.58	6.89	Yes
Degrees	1.33	1.25	Yes
Current Salary	593.18	632.23	No
Expected Salary	217.16	265.35	No

Table 5
Balance table of control variables

Industry	Total Applicants	% Female	% Male	% Ambiguous
Education	9,264	37%	56%	6%
Public Sector	12,094	36%	59%	5%
Construction	2,445	36%	59%	5%
Ads, PR, Events	7,519	35%	55%	11%
Entertainment, Media	6,065	28%	67%	5%
Transport	15,618	26%	69%	5%
Professional Services	45,894	24%	70%	6%
Supply Chain, Logistics	24,215	24%	71%	6%
IT	18,220	23%	71%	5%
Consumer	27,159	22%	73%	5%
Financial	51,684	21%	74%	5%

(Continued in the next page)

Note:
Total percent may not add up to 100% due to rounding. Some industries have too small a sample size to show reliable percent breakdown.

Table 6 Applicant breakdown by industry (Shortlist data)

Industry	Total Applicants	% Female	% Male	% Ambiguous
Automotive	142	20%	77%	3%
Manufacturing	6,252	17%	78%	5%
Medicine	10,619	16%	79%	5%
Energy and Utilities	42,052	13%	83%	5%
Consumer Goods	141	11%	84%	5%
Renewables & Environment	8,172	8%	86%	5%
E-Learning	25	0%	12%	88%

Table 6 continued Applicant breakdown by industry (Shortlist data)

Occupation	Total Applicants	% Female	% Male	% Ambiguous
Administrative	2,193	25%	69%	5%
Analytics, Business Intelligence	14,179	24%	72%	5%
Business Development	19,155	15%	81%	5%
Consulting	26,903	25%	71%	4%
Customer Service, BPO	5,749	24%	68%	8%
Design, Creative, User Experience	1,014	25%	70%	5%
Education	1,562	34%	62%	5%
Engineering	12,430	7%	87%	6%
Fashion Designing, Merchandising	4,373	17%	77%	6%
Finance, Accounts	21,024	17%	77%	6%
Financial Services, Banking, Investments	29,670	20%	75%	5%
General Business	3,610	19%	77%	4%
Human Resources, Recruitment	15,204	48%	46%	6%
IT Hardware	106	36%	58%	7%
IT Software	26,035	25%	68%	7%
Management	4,313	15%	81%	4%
Marketing	21,699	28%	67%	5%
Marketing, Communications, PR	170	22%	73%	5%
Pre-sales / Technical Sales	2,441	9%	86%	5%
Product Management	565	9%	88%	4%
Program Management	3,741	22%	71%	6%
Project Management	10,309	23%	69%	8%
Project Sales	2,538	9%	87%	4%
Public Relations	6,390	39%	53%	8%
Research	1,554	34%	62%	4%
Sales	32,290	14%	82%	4%
Supply Chain, Logistics	8,159	13%	82%	5%
Training	1,589	45%	49%	6%
Writing, Editing, Content	4,838	50%	42%	8%
Other	2,285	16%	79%	4%

Note:
Total percent may not add up to 100% due to rounding.

Table 7 Applicant breakdown by occupation (Shortlist data)

Appendix C

Word	Effect on percent of female applicants	Significant ($p < 0.05$)
Toptier	0.04	No
Travel	-0.04	Yes
Rural	-0.11	Yes
Field	0.00	No
Hour	0.08	No
Diversity	0.10	No

Table 8 JD elements

Masculine		Feminine	
active	force*	affectionate	kinship
adventurous	greedy	child*	loyal*
aggress*	headstrong	cheer*	modesty
ambitio*	hierarch*	commit*	nag
analy*	hostil*	communal	nurtur*
assert*	implusive	compassion*	pleasant*
athlet*	independen*	connect*	polite
autonom*	individual*	considerate	quiet*
boast*	intellect*	cooperat*	respon*
challeng*	lead*	depend*	sensitiv*
compet*	logic	emotiona*	submissive
confident	objective	empath*	support*
courag*	opinion	flatterable	sympath*
decide	outspoken	gentle	tender*
decisive	persist	honest	together*
decision*	principle*	interpersonal	trust*
determin*	reckless	interdependen*	understand*
dominant	stubborn	interpersona*	warm*
domina*	superior	kind	whin*
	self-confident*		yield*

Note:
Stars indicate that the text followed by any letters are searched. For example, "analy*" matches with "analyst", "analyze", "analysis", etc.

Table 9 Gender-coded words in job descriptions (Gaucher et al., 2011)

Appendix D

Competency Based Assessments

As discussed in the background section, assessments that test the core skills needed for a job is one of the best predictors of on-the-job performance[113]. Additionally, utilizing them in the evaluative stages allows people not to rely as heavily on other aspects of the application or make more subjective evaluations

[113] Schmidt and Hunter, 1998

which are more likely to introduce bias. However, to effectively reduce bias, the scores for these assessments must actively factor in to the evaluative process and reduce the reliance on application elements such as educational attainment which is often not a good predictor job performance and could have been affected by bias and discrimination in the early pipeline. The most accurate way to measure the impact of these assessments in reducing bias would be to run an experiment where shortlists are created with and without the assessments. However, in the absence of that, we try to re-create a shortlist based on experience and education and compare it to a shortlist that also takes assessments into account. To do this, we created an index based on how many of the minimum requirements of the job the candidate met and school tier. We ranked candidates based on this index. Assuming the same number of candidates would have been shortlisted without assessments, we selected the top candidates by rank. We then tested the gender breakdown of the candidates who were selected to be shortlisted based on the index as compared to assessments. We find that there is no evidence of bias at the assessment stage: neither women nor men are harmed in terms of their candidacy based on the assessments.

In addition to testing the way the assessments are being factored into the evaluative stage, it is important to ensure that the design of the assessments themselves do not introduce bias. For example, studies of the Scholastic Aptitude Test (SAT), used

Job Status	Removal Type
No account	Self
Showed interested	Self
Account Creation	Self
Screen	Self/Company*
Assessments Started	Self
Assessments Completed	Self
Application Completed	Company
Shortlist	Company
Company approval	Self/Company*
First Interview	Company
Final Round Interview	Company
Offered	Company
Hired	Self

Table 10 Job status by removal type (Shortlist data)

for admission to college in the United States, found the test to be discriminatory against women because it penalized test-takers for wrong answers. Because men tend to be more risk-loving, they were likely to guess on the test which helped them and therefore penalized women for their more risk-adverse nature; similar results were found with other tests as well. The SAT test writers redesigned it in 2016 to remove the penalty for wrong answers[114]. We analyze test scores by gender and see no difference between women and men on assessment scores when controlling for the assessment, job, and applicant education.

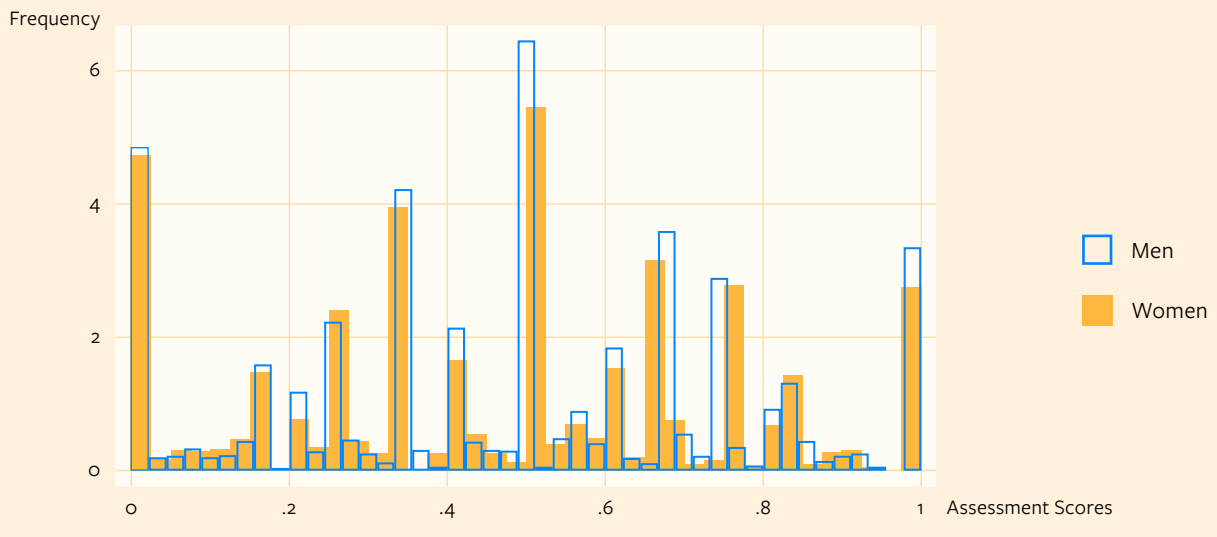
[114] Bohnet, 2016

Two caveats are necessary: as indicated in the last section, it seems that the female applicant pool for Shortlist jobs is more self-selecting than the male one. As a result, it is possible that the women should be performing better than the men on the assessments, however this cannot be gleaned without additional experimenting or data. Additionally, we do not have data to test whether specific elements of the assessments are leading to women being more likely than men to self-remove themselves at the assessment stage.

Cox Survival Analysis Methodology

Cox survival analysis is a methodology that has been primarily used in biology and specifically in epidemiology to study the effect of a disease on different populations. In this framework, patients with a terminal illness are tracked over time. If a patient

Figure 8 Distribution of assessment scores for men and women in Shortlist data



dies, they drop out of the analysis. Time until death is considered to be the variable of interest, and the analysis allows for other factors, such as ethnicity, gender, age, etc. to be controlled for. Two primary functions are used in survival analysis: the survival function and the hazard function. The survival function gives the probability of surviving (or not being rejected from the hiring process) for every time. The hazard function gives the probability that the event will occur (being rejected form the hiring process) given that an individual has survived (or stayed in the process) up until that time[115]. This allows us to test the difference in survival time for two groups (men and women) and provides a relatively straightforward interpretation of the results. In a Cox analysis, the regression coefficients show the proportional hazard for each group. So, in a classic health example, if a group taking Drug A (drug_a = 1) was twice as likely to die as a group taking Drug B (drug_b = 0), the coefficient on the variable drug a would be 2.

[115] Despa, 2018

Survival analysis corrects for two primary limitations that would occur using ordinary least squares analysis:

1. Ssince time is positive, the outcome variable is restricted from being below zero.
2. Observations are right-censored, meaning their survival time is incomplete.

In the context of our data, this means that there are people who have never dropped out of the hiring process, perhaps not because they would not eventually, but because our cross-section shows their status as still in a pending stage because the job they applied for hasn't closed yet. Rather than using time as our variable of interest, we use job status as a proxy for time[116]. We also created a version of job status that specifies at which decision node each applicant drops out, in order to more closely match the assumptions underlying the model. ■

[116] This is more relevant than actual hiring time, which would be influenced by confounding factors at the company-level, such as the efficiency of different HR offices, and at the job-level, such as the length of time the job posting is left available for. Using job status allows us to eliminate the differences in actual time between each step of the process and to focus in on the actual process itself.

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