Gender wage inequality among internal migrants: Evidence from India

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1. Introduction

Understanding the gender wage gap differential has remained an interesting issue among policy makers in both developed and developing countries. The last few decades have witnessed a fall in the gender wage gap mostly in the developed countries (Nicodemo, 2009). Glass-ceiling effect is found by Arulampalam et al. (2007) for eleven European countries, De la Rica et al. (2008) for Spain and Albrecht et al. (2009) for Netherlands. De la Rica et al. (2008) find evidence of glass ceiling effect for the highly educated and glass-floor effect for the less educated. Nordman et al., (2011) find higher wage gap differential across seven West African cities, which have higher gender education gap and female labor force participation. Nicodemo (2009) based on European household panel data finds that the existence of a sticky floor and declining glass ceiling effect and discrimination dominating the characteristic effect.

Several factors have been attributed to the same, which can be broadly grouped into two parts: whether the wage difference is due to differential treatment in the labor market or is it due to differences in productivity. For estimation purposes this has been grouped into an “explained” and a “residual” part. The explained part of the gender wage gap has decreased over time as education and work experience mainly has improved for women. The residual part can be explained by discrimination, lower bargaining power and reduced competition of women. However a factor like “work-place flexibility” is more convincing than the rest (Goldin, 2014).

Studies have examined the gender wage gap between migrant and non-migrants to understand whether migration can play an important role to reduce the gap. Krieg(1990) was one of the earlier studies to examine earning differential by race and gender using the Census data for United States. The study found that migration has a positive and significant impact in reducing wage discrimination. Cooke (2003) finds that the effect of family migration on individual earnings is largely a function of gender. It might increase

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the husband’s income more than the wives even though the latter may have greater potential. Adsera and Chiswick (2007) using panel data for three European countries Germany, Luxemborg and Britain find significant difference in the gender wage gap between immigrants and natives. They conclude that schooling is an important factor for women to increase their pay and for men it is language skills. In the Indian context gender wage gap has been examined for the rural and urban sectors (Agrawal, 2013). We fill this gap in the literature by examining primarily the role of education and skill level in explaining the gender wage gap between migrants and non-migrants in India. We use RIF and unconditional quantile regression analysis to decompose the distributional gender wage differentials among rural urban migrants into the endowment, coefficient and discrimination effects. We examine the same across the following groups: (i) migrants and non-migrants; (ii) urban male and female migrants (as migration to urban areas is more attractive than to rural areas); (iii) industry type; (iv) occupational groups ; (v) level of education ; (vi) type of migration: short-term or regular migration; and (vii) formal and informal activities. Our objective is to understand to what extent these different factors have affected the wage differential and identify suitable policy prescriptions.

2. Data

The analysis is based on the sixty-fourth round of the National Sample Survey on Employment and Unemployment and Migration Particulars conducted from July 2007 to June 2008 across 35 states of India. The survey covered a sample of 79,091 rural and 46,487 urban households, collecting information on a total of 374,294 rural and 197,960 urban individuals. In addition to household characteristics, detailed information on demographic and socio-economic characteristics of the members was also collected.

From the view point of migration, the question is asked in the context of the household and the individual. At the level of the household, identification of who migrated to the village/town of enumeration during the last 365 days preceding the survey is possible. They are termed as the migrant households. A household member whose last usual place of residence is different from the present place of enumeration is considered as a migrant member in a household. The usual place of residence of a person is defined as a place (village/town) where he/she has stayed continuously for a period of six months or more.

3. Empirical methodology

Studies analyzing the gender wage gap usually employ the Oaxaca-Blinder decomposition technique for estimation purposes. However as identified in Firpo et al. (2007) there are certain limitations of the Oaxaca-Blinder decomposition technique (Oaxaca, 1973). The most important limitation is that it cannot be used to divide the composition effect for each covariate. This means that we cannot answer the question that
whether changes in the distribution of a particular covariate has led to a rise in wage inequality. To answer this question we need to use the unconditional quantile regression and quantile decomposition techniques based on Firpo et al. (2009). Unlike the case of conditional quantile regression (Koenker and Bassett, 1978) we can examine the impact of a change in X on the corresponding quantiles of the unconditional distribution of Y. The influence function (IF) is used widely for this purpose. It is the influence of a particular observation on a measure of distribution say a quantile. If added back to the quantile we obtain the recentred influence function (RIF). It is denoted by:

\[ IF(Y, q_\tau) = \frac{(r-I(y \leq q_\tau))}{f_y(q_\tau)} \]  

where \( q_\tau \) is the \( \tau \)th quantile of Y,I is the indicator function and \( f_Y \) is the density of the marginal distribution of Y. Then RIF \( (Y, q_\tau) = q_\tau + IF(Y, q_\tau) \). The decomposition is as follows:

\[ \overline{RIF}(Y_m, \overline{q}_{mt}) - \overline{RIF}(Y_f, \overline{q}_{ft}) = (\overline{X}_m - \overline{X}_f)\overline{p}_\tau + [\overline{X}_m(\beta_{mt} - \overline{p}_\tau) - \overline{X}_m(\beta_{ft} - \overline{p}_\tau)] \]  

where \( \overline{q}_{mt} \) and \( \overline{q}_{ft} \) are the \( \tau \)th quantiles of the marginal distributions of \( Y_m \) and \( Y_f \). \( \beta_{mt} \) and \( \beta_{ft} \) are the coefficient estimates from RIF-OLS regression for male and female. \( \overline{p}_\tau \) is the non-discriminatory wage structure at the \( \tau \)th quantile from pooled RIF-OLS regression estimated. \( \overline{X}_m - \overline{X}_f \) is the endowment effect and \( X_m(\beta_{mt} - \overline{p}_\tau) - X_m(\beta_{ft} - \overline{p}_\tau) \) is the discrimination effect at the \( \tau \)th quantile, which can be further decomposed into :men’s advantage \( \overline{X}_m(\beta_{mt} - \overline{p}_\tau) \) and \( -X_m(\beta_{ft} - \overline{p}_\tau) \) is the women’s disadvantage. The mean of RIF\( (Y, q_\tau) = q_\tau \) and the mean differences in RIF \( (Y, q_\tau) \) is equivalent to the difference in \( q_\tau \) (Firpo et al., 2009).

\[ q_{mt} - q_{ft} = \overline{RIF}(Y_m, \overline{q}_{mt}) - \overline{RIF}(Y_f, \overline{q}_{ft}) = (\overline{X}_m - \overline{X}_f)\overline{p}_\tau + [\overline{X}_m(\beta_{mt} - \overline{p}_\tau) - \overline{X}_m(\beta_{ft} - \overline{p}_\tau)] \]

We follow the procedure adopted by Magnani and Zhu (2012). We firstly conduct an unconditional quantile regression for males and female in urban India. The dependent variable is the logarithm of wages. The independent variables are household type (self-employed, regular wage/salary earning, casual labour, others), social group (scheduled caste, scheduled tribe, other backward classes, and others), religion (Hindu, Muslim, Christian, Others), level of education, skill type, migration status and state region level dummies. We RIF estimates are pooled for both the genders and an Oaxaca decomposition analysis conducted. In the Oaxaca decomposition exercise we correct for selection bias by using the Heckman sample selection method (Heckman, 1976; 1979,
Jann, 2008). Thus labor force participation is a function of individual characteristics like the age and age squared and household demographic characteristics like number of family members in the household in the age group of 0-6, 7-14, 15-24, 25-59 and 60 years and above. The dependent variable for Oaxaca decomposition is the pooled RIF estimates and the independent variables are the same as the case of RIF regression.

4. Main findings

Our preliminary finding is that there is the presence of both sticky floor and glass-ceiling effect observed for urban migrants as compared to the non-migrants (Table 1). We find a U–shaped relationship for the returns or coefficient effect across the gender wage gap distribution (Figure 1). The coefficient effect is due to discrimination in the labor market. We find positive significant effect all thorough the distributional wage gap. Thus though the gender wage gap does not reflect a better-off situation for the migrants there is a fall in the wage gap across the distribution almost till the third quartile. This is in line with the literature whereby studies have found that for the case of say technical jobs the discrimination observed is more given factors like work-flexibility and high end skills in which women lag behind and hence the glass-ceiling effect. However for the case of say clerical jobs lower skill requirement reduces the scope for discrimination between the two groups and thus the sticky floor effect. Further work involves understanding if there has been any improvement in the living standards for the “fairer sex” on move using Sen’s capability approach.

References:


Table 1: Oaxaca decomposition of male female wage differential
Migrant vs non-migrant (Urban sector)

<table>
<thead>
<tr>
<th>Quantile</th>
<th>Coefficient effect</th>
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<tbody>
<tr>
<td></td>
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<tr>
<td>10</td>
<td>0.0905***</td>
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<td>20</td>
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<tr>
<td>30</td>
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<td>(0.0203)</td>
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<td>(0.0210)</td>
</tr>
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<td>50</td>
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<td>(0.0241)</td>
</tr>
<tr>
<td>60</td>
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<tr>
<td>70</td>
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<td>(0.0272)</td>
</tr>
<tr>
<td>80</td>
<td>0.1060***</td>
<td>(0.0277)</td>
</tr>
<tr>
<td>90</td>
<td>0.1244***</td>
<td>(0.0297)</td>
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Standard errors are reported in parenthesis
Significance level: *** p<0.01, ** p<0.05, * p<0.1