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Wage Discrimination in India's Informal Labor Markets: Exploring the Impact of Caste and Gender

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Abstract

Although there has been considerable interest in wage discrimination in India, available studies have largely dealt with formal rather than informal markets that are of little relevance for the poorest people. Focusing on India's informal labor markets leads to three findings of interest. First, gender wage discrimination is larger in informal than in formal labor markets, resulting in losses that are larger than receipts from one of the country's most important safety-net programs. Second, economic growth will not make gender discrimination in wage labor markets disappear. Finally, contrary to what is found for gender, the hypothesis of no significant wage discrimination based on caste cannot be rejected.

1. Introduction

Discrimination, defined as a systematic gap in rewards to factors of production that is due to easily identifiable, though economically irrelevant group characteristics (e.g. skin color or gender), has long attracted the attention of economists. Even if it implies sub-optimal outcomes, a caste-based equilibrium can be self-fulfilling and persistent over time (Akerlof, 1975). While competition can make discrimination disappear (Becker, 1971), it may persist even in developed countries (Holzer and Neumark, 2000). Moreover, discriminatory practices affect not only current outcomes but also groups' social identities and their long-term potential (Hoff and Pandey, 2006).

Economic study of discrimination is thus motivated by the moral case for equal treatment and the potentially far-reaching growth-reducing impacts of discrimination. The latter arise because discrimination will affect labor supply and lead to underutilization of valuable resources (Klasen, 2002). This can distort incentives for investment, e.g. in education of girls versus boys based on an expectation that these returns may be different (Alderman and King, 1998). As a result, inequality traps where a disadvantaged group faces a long-run opportunity set much worse than that of another group even though a better set would be possible (Bourguignon et al., 2007), can arise.

Reinforced by a social order built on endogamous castes—originally based on occupation—often reinforced by residential segregation, discrimination is particularly pronounced in India. While caste is losing its relevance for occupational choice in many urban centers, it continues to exert influence in rural areas of India, especially Northern ones (Hoff and Pandey, 2006). Caste differences and prejudices may be

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reinforced by gaps in land and human capital endowments (Deshpande, 2001) or long-standing bias against females as manifest, for example, in female infanticide (Gleason, 2003). Although the undesirable impacts are well understood, overcoming discrimination is not easy, partly because efforts at affirmative action often become embroiled in politics (Deshpande, 2007).

Efforts to quantify the extent of discrimination in India and its evolution over time will thus be of policy relevance. While some studies have explored statistical discrimination in wages, they focus on the formal sector only, thus leaving out the roughly 70% of India's population living in rural areas. This is important because, unless they have access to resources such as land and capital to allow self-employment, most rural poor have to rely on casual and informal labor markets to survive. In addition to volatility, e.g. due to climatic shocks, discrimination in these markets will affect the welfare and scope for investment by the poorest groups in society.

We use a nationally representative household survey to extend analysis of wage discrimination to the informal sector, focusing on three questions, namely to (i) quantify the size of discrimination in casual labor markets compared to what is found in formal settings; (ii) explore whether caste- or gender-based discrimination is more important; and (iii) compare discrimination in villages with high and low income levels. Results suggest that: (i) discrimination in informal markets is more pronounced than in formal ones; compared to less than 30% of gender wage gaps in formal labor markets (Jacob, 2006), 61% of gender wage gaps for all casual workers and 76% of the gap for agricultural workers is attributable to discrimination; (ii) wage differences between scheduled castes and tribes (SC/STs)[1] and the rest of the population reflect differences in endowments rather than discrimination; and (iii) gender discrimination in rich villages is higher than in poor villages so that growth alone may not make it disappear, as has been found for dowries (Anderson, 2003).

This implies that ways to improve outcomes for women in casual labor markets may be justified. Initiatives to expand women's access to productive assets, e.g. through inheritance legislation such as recent reforms of the Hindu Succession Act, measures that make it easier to rent land, or credit access via self-help groups, all go in this direction. Research to assess the extent to which these measures' affect discrimination and female empowerment is desirable.

The paper is structured as follows. Section 2 draws on the literature to set out our conceptual framework and approach. Section 3 presents data and uses descriptive evidence to highlight caste- and gender differences in India's informal sector. Section 4 presents results from wage regressions in agriculture and non-agriculture and decomposition of wage differentials. Section 5 concludes with a number of policy implications.

2. Motivation and Framework

The literature points to continued relevance of gender and caste differentials. We thus discuss techniques to decompose differences in wage rates as well as the assumptions about the "unbiased" situation underpinning them. This links to a discussion of the estimation strategy, in particular strategies to control for selection, used in subsequent sections of the paper.

Discrimination: Empirical Evidence and Policy Implications

Since wage discrimination, defined as the gap in earnings between different types of workers that remains once all observable characteristics have been accounted for

(Blau and Kahn, 2000), was put on the economists' agenda (Becker, 1971), it has been studied extensively. In addition to direct effects, it can reduce human capital accumulation (Alderman and King, 1998), technology adoption, overall growth, and equilibrium wage rates (Seguino, 2000). The impact of under-investment in female human capital can be large and persistent if female human capital is linked to non-economic benefits such as lower fertility or better child care and education (Klasen, 2002) and government action to counter it could be justified (Bourguignon et al., 2007). In the US, the extent of gender discrimination decreased significantly during the last century (Blau and Kahn, 2004) with most of the reduction attributable to the opening up of occupations to women and more meritocratic labor markets (Goldin, 2002). There is also evidence that discrimination decreases with education (Montgomery and Powell, 2003) although male participation at the very top of the earnings distribution remains larger than that of females (Gneezy et al., 2003).

In India, gender interacts with caste, an originally occupation-based endogamous institution that continues to permeate society (Anderson 2003).[2] To counter persistent discrimination, the 1950 Constitution puts in place a system of affirmative action to reserve a share of government jobs for members of SCs and STs (Deshpande 2007). The 73rd Constitutional amendment in 1992 extends this to politics by requiring a proportion of seats at all political levels to be reserved for STs, SCs and women (Chattopadhyay and Duflo, 2004). However, laws are often not enough to overcome a legacy of prejudice (Hoff and Pandey, 2006) or residential segregation (Besley and Burgess, 2004; Kijima, 2006) and some studies have concluded that policies to improve affected groups' endowments might have been more effective (Borooah et al., 2007).

Cross-sectional regressions point towards potentially large effects of gender discrimination; it is estimated that a 10% increase in the female to male worker ratio could increase net domestic product by 8% (Kingdon and Unni, 2001) and that raising levels of female employment nationally to those in Karnataka, the most advanced state, could increase output by 45% (Esteve-Volart, 2004).[3] More precise measures can be derived from wage regressions and decomposition techniques. A study of Delhi's informal urban labor markets in the 1970s finds significant caste-discrimination of some 7% (Banerjee and Knight, 1985). A nationally representative 1994 survey points to effects of 32–36% for SCs and 39–46% for STs (Borooah, 2005).[4] Nationally, the level of gender discrimination is estimated to have dropped from 36–51% to 27–30% in the 1983–1999 period, compared with 0–3% for caste (Jacob, 2006). All the above studies focus exclusively on the formal sector and neglect selectivity issues due to the fact that participation in wage employment is a choice rather than exogenously given. Before discussing how our data allow us to address these issues, we lay out the methodology to deal with this explicitly.

Conceptual Framework

The primary method of analyzing wage differentials between any two groups, e.g. black versus white, male versus female, or high caste versus low caste, is to decompose observed wage differentials into those attributable to productivity or observed characteristics and those due to discrimination (Oaxaca, 1973; Blinder, 1973; Sung et al., 2001; Rozelle et al., 2002). Both are obtained from wage regressions. As the econometric framework for gender discrimination can be applied to the study of caste discrimination, we concentrate on the former. Letting individuals be indexed by i, $\ln(w_m)$ and $\ln(w_f)$ denote the log of male (m) and female (f) wage rates, respectively, we estimate:

$$\ln(w_m) = \boldsymbol{\beta}_m \boldsymbol{X}_m + \varepsilon_m, \tag{1}$$

$$\ln(w_f) = \boldsymbol{\beta}_f \boldsymbol{X}_f + \varepsilon_f, \tag{2}$$

where $\boldsymbol{X_i}$ is a vector of individual, household and community characteristics that determines i's potential wage rate, $\boldsymbol{\beta}_i$ is a vector of parameters to be estimated, and ε_i is the i.i.d error term. The difference in average daily wage rates between males and females can then be expressed as:

$$\ln(\bar{w}_m) - \ln(\bar{w}_f) = \hat{\beta}_m \bar{X}_m - \hat{\beta}_f \bar{X}_f \tag{3}$$

which, by adding and subtracting $\hat{\beta}_m \bar{X}_f$, can be transformed into:

$$\ln(\bar{w}_m) - \ln(\bar{w}_f) = \hat{\beta}_m (\bar{X}_m - \bar{X}_f) + (\hat{\beta}_m - \hat{\beta}_f)\bar{X}_f. \tag{4}$$

Assuming that without discrimination the male wage structure applied for males and females, the first term on the right-hand side of (4) corresponds to the gender wage differential arising from differences in characteristics whereas the second term denotes the discrimination component that arises from wage differentials due to different returns to these characteristics.

Assumptions about the non-discriminatory wage structure will lead to decomposition methods other than (4) with different results (Oaxaca, 1973; Oaxaca and Ransom, 1994). For example, adding and subtracting a term ($\hat{\beta}_f \bar{X}_m$) to the right-hand side of (3) gives:

$$\ln(\bar{w}_m) - \ln(\bar{w}_f) = \hat{\beta}_f (\bar{X}_m - \bar{X}_f) + (\hat{\beta}_m - \hat{\beta}_f)\bar{X}_m, \tag{5}$$

based on the assumption that, in the absence of discrimination, the female wage structure will prevail. Below, we refer to (4) and (5) as Oaxaca–Blinder I and II decompositions, respectively.

Assumptions on recovering the parameter vector $\boldsymbol{\beta}$ for the "non-discriminatory" wage structure will give rise to another class of decompositions. If one assumes that the wage structure without discrimination falls between the pure male and female structure, one can use either $\boldsymbol{\beta}$ from OLS estimation on a pooled male–female sample (Neumark, 1988) or a population weighted average of $\hat{\beta}_m$ and $\hat{\beta}_f$ (Cotton, 1988). Formally, we add and subtract the term ($\beta \bar{X}_m - \beta \bar{X}_f$) to the right-hand side of (3) to obtain:

$$\ln(\bar{w}_m) - \ln(\bar{w}_f) = \beta(\bar{X}_m - \bar{X}_f) + (\hat{\beta}_m - \beta)\bar{X}_m - (\beta - \hat{\beta}_f)\bar{X}_f. \tag{6}$$

As earlier, the first term on the right-hand side reflects wage differentials due to different characteristics. In contrast to the Oaxaca–Blinder decompositions, however, discrimination-induced wage differentials are now decomposed into two terms, the "advantage of being male" and the "disadvantage of being female". It follows from (6) that the first of these is the difference between actual wages received by males and the hypothetical wage they would have received in the absence of discrimination while the second term refers to the difference between the wage females would have received without discrimination and what they actually received. We will refer to these methods, which differ from each other only in the assumptions made on the "non-discriminatory" coefficient vector, as Neumark's method and Cotton's method.

Estimation Strategy

While many studies used simple OLS to recover the respective coefficient vectors, failure to deal with selectivity may bias results (Gronau, 1977). This will be of concern in developing countries where female non-participation is higher than in developing ones. To obtain consistent estimates of the wage equation, we use a two-step approach and first estimate individuals' participation in wage employment using a standard "first stage" probit regression (Heckman, 1979). Define

$$y_i^* = \gamma \boldsymbol{X_i} + \delta \boldsymbol{L_i} + \boldsymbol{\eta}_i, \quad y_i = 1 \quad \text{if } y_i^* > 0 \text{ and } y_i = 0 \text{ otherwise,} \tag{7}$$

where y_i is a dummy that equals 1 if individual i participated in wage labor and 0 otherwise, $\boldsymbol{X}_i$, is a vector of individual, household and community attributes that affect participation in wage labor markets and wage earnings, $\boldsymbol{L}_i$ is a vector of household characteristics that affect participation but not wage earnings, η_i is an *iid* error term, and γ and δ are coefficient vectors to be estimated.

The vector $\boldsymbol{X}_i$ includes member-, household- and community-level variables. Member attributes include gender, formal education as a proxy for human capital, and age to measure experience. At household level, we include the value of assets owned and a caste dummy. In our context, these will affect individuals' self-employment opportunities and thus the reservation wage they will be willing to accept in labor markets. Village income is included at the community level as it will affect local wage levels. Variables included in $\boldsymbol{L}_i$ affecting the probability of entering wage employment but not wages are level (and square) of the dependency ratio and households' land endowment. Without panel data to control for unobserved individual characteristics, we use village-level dummies to control for unobserved social and economic factors at the local level.

Use of the parameters estimated in (7) allows us to construct the inverse Mills ratio λ_i for each observation:

$$\lambda_i = \phi(\gamma \boldsymbol{X}_i + \delta L_i)/\Phi(\gamma \boldsymbol{X}_i + \delta L_i), \tag{8}$$

where ϕ and Φ are the standard normal density and standard normal distribution function. Adding λ_i as an additional explanatory variable in the "second stage" wage equation yields:

$$\ln(W_i) = \beta \boldsymbol{X}_i + \rho \lambda_i + \varepsilon_i. \tag{9}$$

Choosing the inverse Mills ratio for the sample under concern (i.e. male, female or pooled samples), the expression for wage differentials can then be written as:

$$\ln(\bar{w}_m) - \ln(\bar{w}_f) = \left(\hat{\beta}_m \bar{X}_m - \hat{\beta}_f \bar{X}_f\right) + \left(\hat{\rho}_m \bar{\lambda}_m - \hat{\rho}_f \bar{\lambda}_f\right), \tag{10}$$

where $\hat{\rho}_m$ and $\hat{\rho}_f$ are corresponding coefficients of λ_i. We add selectivity corrections following Reimers (1983). For example, the Oaxaca–Blinder I decomposition (4) is transformed into:

$$\ln(\bar{w}_m) - \ln(\bar{w}_f) = \hat{\beta}_m(\bar{X}_m - \bar{X}_f) + (\hat{\beta}_m - \hat{\beta}_f)\bar{X}_f + (\hat{\rho}_m \bar{\lambda}_m - \hat{\rho}_f \bar{\lambda}_f), \tag{11}$$

and inclusion of $(\hat{\rho}_m \bar{\lambda}_m - \hat{\rho}_f \bar{\lambda}_f)$ into equations (5) and (6) is done correspondingly.[5] These results may also imply that methods based on weighted non-discriminatory wage structure give more accurate estimates than Oaxaca–Blinder methods because neither the male nor the female wage can be assumed to correspond to the wage structure in the absence of discrimination.

3. Descriptive Evidence

Before presenting the econometrics and decomposition results, we highlight differences in wages received between gender- and caste-groups. Somewhat surprisingly, gender–wage gaps in casual labor markets are found to be much more pronounced than caste-based wage differences. More detailed exploration of the incidence and nature of discrimination is thus warranted.

Data and Key Household Characteristics

Our empirical estimates draw on a nationally representative survey of slightly fewer than 7,500 rural Indian households with about 30,000 individuals aged 14 or above in 240 Indian villages in 12 states by the Indian National Council for Applied Economic Research (NCAER) in 1999.[6] This is one of few datasets in India containing gender-disaggregated wage rates.

The two top panels of Table 1 illustrate household characteristics and asset composition. At about 24% who are landless and 18% who are SC/STs, averages are close to the national mean. Still, with 27% and 25%, respectively, SC/STs are concentrated in the landless and the bottom quintile and, with a Gini coefficient of 0.78 (or 0.66 for land owners only), inequality in land access remains high. Heads' human capital (2.9 versus 5.9 years of schooling for bottom versus top quintile) and non-land assets are also unequally distributed. With 0.56, the Gini coefficient for non-land assets is lower than that for land, with a mean of Rs 195,255 as compared to 90,453 for the landless and 81,122 for the bottom and 368,473 for the top quartile. Those at the top own more than four times the amount of assets than those in the bottom quartile. Caste inequality is also high. ST/SCs are more likely to be landless (36% versus 21%) and, even if they are not, have lower endowments of land (2.6 versus 4.3 acres) and human capital (education of the head is 3.3 versus 4.5 years) and non-land assets (Rs. 127,821 versus Rs. 209,834) than the rest of the population.[7]

These differences translate not only into income inequality, with Ginis of 0.52 and 0.30 for per capita income and consumption, but also disproportionate reliance on casual wage labor that makes the poor vulnerable to fluctuating labor demand and discrimination.[8] The landless rely on casual wages for more than three fifths (61%) of income as compared to one fifth for the landed.[9] The bottom panel of Table 1 illustrates that households in the top quartile worked 52 days versus 244 days for those in the bottom quartile. Similarly, ST/SC households spent 244 days compared to 132 days of wage work for non-ST/SC households.

Wage Differentials by Gender and Caste

To assess the potential impact of wage differentials by gender and caste, and to also make inferences on whether wage discrimination may be present in agriculture or

Table 1: Key Household Characteristics

		By Landownership		*By Consumption*		*By Caste*	
	Total	*Landed*	*Landless*	*Top Quartile*	*Bottom Quartile*	*Non-SC/ST*	*SC/ST*
Household characteristics							
Household size	6.02	6.25	5.29	4.86	7.52	6.09	5.70
Number of family members <14 years old	1.86	1.88	1.79	1.05	2.91	1.85	1.88
Number of family members 14–60 years old	3.75	3.92	3.22	3.37	4.22	3.81	3.47
Head's age	49.20	50.46	45.17	51.24	47.71	49.62	47.26
Years of education by head	4.28	4.49	3.59	5.98	2.93	4.50	3.25
Land owned (acres)	3.97	5.22	0.00	6.40	2.33	4.27	2.61
Landless households (%)	23.84	0.00	100.00	13.48	32.99	21.25	35.82
ST/SC (%)	17.78	14.98	26.71	11.18	25.08	0.00	100.00
Other backward castes (%)	22.75	24.03	18.69	22.15	24.28	27.67	0.00
Value and distribution of non-land assets							
Value of non-land assets (Rs)	195,255	228,053	90,453	368,473	81,122	209,834	127,821
Of which house (%)	54.69	51.67	64.34	47.19	63.64	54.02	57.78
Of which financial assets (%)	21.24	21.74	19.65	24.61	16.61	21.44	20.32
Of which farming assets (%)	13.45	16.31	4.31	15.93	10.21	13.86	11.58
Of which consumer durables (%)	10.62	10.28	11.70	12.27	9.55	10.68	10.32
Income and its sources							
Total per capita consumption (Rs/year)	6,583	6,968	5,354	12,130	3,143	6,758	5,777
Total household income (Rs/year)	58,155	65,970	33,185	109,394	27,979	61,496	42,703
Total income per capita (Rs/year)	10,646	11,880	6,704	22,689	3,682	11,119	8,459
.. of which from crop production (%)	39.87	51.37	2.90	43.44	33.07	41.55	32.08
.. of which from livestock production (%)	9.51	10.29	6.99	10.87	6.82	9.95	7.47
.. of which from wage work (%)	28.75	18.68	61.12	10.85	47.26	25.29	44.83
Agricultural casual labor (%)	16.07	10.08	35.32	6.00	26.37	13.52	27.95
Non-agricultural casual labor (%)	12.68	8.60	25.79	4.85	20.90	11.77	16.88
.. of which from salaried work (%)	12.04	11.86	12.62	22.27	4.91	12.82	8.42
.. of which from self-employment, transfer(%)	10.28	8.74	15.24	12.99	7.37	10.86	7.60
Household level participation							
Total days worked	301.69	279.58	372.34	226.58	367.69	289.85	356.47
Days spent on wage labor	149.74	107.32	285.26	52.01	244.07	132.36	230.12
Share of days spent on wage work (%)	36.44	25.67	72.68	14.71	55.73	32.54	54.39
Female participation (%)	25.75	24.89	27.04	23.89	25.19	23.62	31.88
Number of observations	7,476	5,694	1,782	1,869	1,870	6,147	1,329

Note: Farming assets include livestock.
Source: Own calculation from NCAER REDS Survey.

non-agriculture, Table 2 compares descriptive statistics from our survey on wages by gender (top panel) and caste (bottom panel). For both agricultural and non-agricultural work, individuals are hired on a per-day basis rather than on piece rates. Nationally, females received 28% less for casual labor in agriculture (33 versus 46 Rs/day) and 35% in non-agriculture (40 versus 62 Rs/day).[10] Across regions,

Table 2: Wage Rates (Rs/Day) for Casual Labor in Agriculture and Non-agriculture by Gender qnd Caste

	Agricultural Casual Labor			*Non-Agricultural Casual Labor*		
	By Gender					
	Male	*Female*	*Difference*	*Male*	*Female*	*Difference*
National	46.49	33.26	28.46%***	62.12	40.46	34.87%***
North	57.29	50.65	11.59%***	72.15	58.46	18.97%***
West	38.27	30.71	19.77%***	60.54	37.58	37.93%***
East	42.06	33.45	20.47%***	49.24	35.13	28.66%***
South	52.53	33.73	35.79%***	75.56	43.33	42.65%***
No. of obs.	2,322	1,699		1,986	522	
	By Caste					
	Non ST/SC	*ST/SC*	*Difference*	*Non ST/SC*	*ST/SC*	*Difference*
National	42.50	37.86	10.92%***	59.42	53.31	10.28%***
North	57.90	48.26	16.66%***	71.65	70.15	2.09%
West	34.59	34.56	0.08%	57.77	50.99	11.74%***
East	39.72	38.16	3.92%*	47.02	48.41	–2.96%
South	47.58	39.22	17.57%***	69.80	48.73	30.18%***
No. of obs.						

Note: Statistical significance of the difference between male and female rates indicated as follows: *** = significant at 1%; ** = significant at 5%; * = significant at 10%. 1 US$ equals about 42 INR at the time of the survey.
Source: Own calculation from NCAER 1999 REDS Survey.

gender–wage differentials are significant everywhere and greater than 20% (for agriculture) or 29% (for non-agriculture) everywhere except the North. Table 2 also shows that caste-related wage gaps are much smaller and less consistent across regions than those by gender. The daily wage for SCs/STs is between 10% and 11% lower than that received by others (38 versus 43 Rs/day and 53 versus 59 Rs/day). Variability across regions is greater as well; caste differences are most marginally significant for agriculture in the West and the East and for non-agriculture in the North and the East. In the South, where caste-wage differentials are most pronounced, with 18% and 30% for agriculture and non-agriculture, respectively, their magnitude is significantly below the gender wage gap ascertained earlier.

The above points towards discrimination in informal labor markets with gender being more important than caste. At the same time, it does not adjust for selection into wage employment or individual characteristics, all of which will require a more rigorous econometric approach.

4. Econometric Results

Estimation of wage determinants and decomposition of wage differentials into their different components suggests that gender but not caste discrimination is highly significant throughout India. Even with conservative assumptions, losses due to gender discrimination by far exceed benefits from the public distribution system, one of the Government's largest anti-poverty programs.

Labor Market Participation and Wage Determinants

Results from participation and wage regressions, respectively, in the form of marginal probabilities, are reported in the bottom and top panels of Table 3. Participation regressions point towards lack of assets and alternative opportunities as key reasons for households to take up wage labor, consistent with descriptive evidence. An extra year of education is estimated to reduce the propensity for participation in casual labor markets by 2%. A 50% reduction of assets (R 83,566) would increase the probability of participation by about 2.6% percentage points. The probability of taking up wage work is estimated to peak at an age of about 35 years while the impact of the dependency ratio is estimated to be U-shaped and to decrease up to a value of 0.24. At the mean of all right-hand side variables, predicted rates of participation are significantly higher for males than for females and for SC/STs as compared to the rest.

Casual wage workers are not only poorer than the average; they also live in poor areas. Estimated coefficients on caste, dependency ratio, age and education in the case of gender and for gender, age, assets, land, village income and dependency ratio in the case of caste are lower for females than for males or for non-scheduled versus scheduled castes. This implies that, although women are less likely to participate in casual labor, exogenous changes are less likely to prompt them to give up work. The opposite is true for caste; while those in the SC/ST category are more likely to participate in casual work than the average, changes in their own assets, land area, or of village-level income will be more effective in prompting them to quit casual wage work.

Determinants of wages received are displayed in the top panel. With an estimated wage that is lower by 14 percentage points, agricultural workers receive considerably less than those in non-agriculture. The positive and significant coefficient on education suggests that an extra year of education would increase wages by about 1.5%. We also find evidence of positive returns to experience, proxied by age, which is estimated to increase, though at a decreasing rate, up to an age of about 50 years.[11] Finally, with a coefficient of –2%, individuals from scheduled castes or tribes are estimated to receive lower wages than others once other characteristics are adjusted for.[12] Similarly, with coefficients of 0.26 to 0.31 for the male dummies in columns 4 and 5, males are estimated to receive much higher wage than females other factors being held constant. The significance of the inverse Mills ratio suggests that failure to adjust for the probability of participation would lead to biased estimates.

Decomposition of Wage Differentials by Gender and Caste

Decomposing wage differentials by gender (Table 4) and caste (Table 5) overall in the top panel and for agricultural as well as non-agricultural wages in the 2nd and 3rd panels, respectively, points to two regularities. Consistent across methodologies, the lion's share of the large observed wage differentials between males and females is attributed to discrimination rather than productivity gaps or selectivity bias. In fact, bootstrapped standard errors in each case suggest that we are unable to reject the hypothesis of no caste discrimination in informal labor markets.[13] Splitting the sample into agricultural and non-agricultural wage earners also suggests that discrimination is more pronounced in the agricultural sector than the non-agricultural sector.[14] The

Table 3: Determinants of Participation in Casual Labor and Daily Wage Received

	Total Sample	Male	Female	Non-SC/ST	SC/ST
	Wage Determinants (2nd stage regression)				
Education (years)	0.015***	0.003**	0.001	0.003**	0.003*
	(14.77)	(2.29)	(0.34)	(2.03)	(1.70)
Value of total assets/1,000,000	0.003	0.008	0.016	0.002	–0.203
	(0.13)	(0.36)	(0.13)	(0.12)	(0.87)
Age	0.016***	0.020***	0.008***	0.015***	0.019***
	(10.06)	(11.71)	(2.94)	(8.77)	(6.08)
Age squared	–0.000***	–0.000***	–0.000***	–0.000***	–0.000***
	(8.77)	(10.93)	(2.81)	(8.12)	(5.87)
Village per capita income/1000	0.072***	0.078***	0.025	0.071***	0.054***
	(3.72)	(4.96)	(0.80)	(3.14)	(3.32)
Dummy for agricultural wage worker	–0.141***	–0.125***	–0.050***	–0.113***	–0.093***
	(15.72)	(13.35)	(3.49)	(11.59)	(6.05)
ST/SC dummy	–0.016	–0.010	–0.002		
	(1.55)	(0.95)	(0.11)		
Male dummy				0.314***	0.264***
				(24.46)	(13.98)
Inverse Mills ratio	0.031**	0.039**	0.027	0.029**	0.057
	(2.31)	(2.56)	(1.12)	(2.02)	(1.48)
Observations	29158	15118	14040	24396	4762
	Selection Equation (1st stage regression)				
Education (years)	–0.020***	–0.035***	–0.012***	–0.020***	–0.022***
	(14.36)	(8.84)	(7.37)	(9.25)	(5.53)
Value of total assets/1,000,000	–0.631***	–0.262***	–0.704***	–0.154***	–3.321***
	(11.82)	(4.36)	(7.20)	(4.48)	(6.12)
Age	0.060***	0.041***	0.018***	0.022***	0.054***
	(16.08)	(8.95)	(7.56)	(9.23)	(6.75)
Age squared	–0.001***	–0.001***	–0.000***	–0.000***	–0.001***
	(16.10)	(9.00)	(7.60)	(9.29)	(6.82)
Village per capita income/1000	–0.029***	–0.009**	0.001	0.001	0.053*
	(8.97)	(2.10)	(0.69)	(0.29)	(1.83)
Male member				0.289***	0.378***
				(9.50)	(6.42)
SC/ST dummy	0.313***	0.182***	0.082***		
	(14.53)	(7.65)	(6.73)		
Dependent ratio	–0.276***	–0.192***	–0.071***	–0.094***	–0.106
	(8.04)	(3.69)	(3.33)	(3.57)	(1.01)
Dependent ratio squared	0.584***	0.459***	0.186***	0.245***	0.378**
	(10.13)	(5.11)	(4.97)	(5.32)	(2.45)
Total land area	–0.095***	–0.066***	–0.022***	–0.035***	–0.057***
	(15.80)	(9.03)	(8.21)	(9.78)	(5.79)
Observations	28680	14872	12468	23647	4585

Notes: Robust z-statistics in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1% level. Village dummies were included to control for the village level heterogeneity.

Table 4: Decomposition of Male and Female Wage Differentials

	Oaxaca–Blinder I	*Oaxaca–Blinder II*	*Neumark*	*Cotton*
All workers				
Observed wage differences	0.411	0.411	0.411	0.411
Productivity gap	0.119***	0.134***	0.196***	0.124***
	(12.24)	(6.66)	(22.45)	(12.48)
Discrimination gap	0.280***	0.266***	0.203***	0.275***
	(8.92)	(5.95)	(6.56)	(7.92)
Male advantage gap	n.a.	n.a.	0.067***	0.086***
			(7.17)	(5.98)
Female disadvantage gap	n.a.	n.a.	0.136***	0.194***
			(4.71)	(5.39)
Selectivity gap	0.027	0.027	0.027	0.027
	(1.03)	(1.03)	(1.03)	(1.03)
Agricultural workers only				
Observed wage differences	0.334	0.334	0.334	0.334
Productivity gap	0.044***	0.079***	0.124***	0.059***
	(4.24)	(2.92)	(12.32)	(4.28)
Discrimination gap	0.229***	0.194***	0.150***	0.215***
	(5.11)	(3.12)	(3.22)	(4.22)
Male advantage gap	n.a.	n.a.	0.071***	0.080***
			(3.80)	(3.12)
Female disadvantage gap	n.a.	n.a.	0.079**	0.079**
			(2.06)	(2.46)
Selectivity gap	0.061	0.061	0.061	0.061
	(1.47)	(1.47)	(1.47)	(1.47)
Non-agricultural workers only				
Observed wage differences	0.414	0.414	0.414	0.414
Productivity gap	0.070***	0.137**	0.127***	0.082***
	(4.18)	(2.54)	(8.13)	(4.78)
Discrimination gap	0.234	0.166	0.176	0.221
	(1.15)	(0.66)	(0.86)	(1.04)
Male advantage gap	n.a.	n.a.	0.041	0.027
			(1.05)	(0.57)
Female disadvantage gap	n.a.	n.a.	0.135	0.194
			(0.72)	(1.18)
Selectivity gap	0.064	0.064	0.064	0.064
	(0.36)	(0.36)	(0.36)	(0.36)

Note: Figures in parentheses are bootstrapped *t*-statistics based on 500 replications. * significant at 10%; ** significant at 5%; *** significant at 1% level.

predicted male–female wage differential (0.40) is close to the figure that emerged from descriptive evidence (0.41). Of this, 6.5% is attributed to selectivity, between 30% and 48% (depending on the method used) to endowment- or productivity differentials, and the rest—from 68% to 50%—to discrimination. As casual labor markets in our sample are dominated by males (78%), it is reasonable to assume that the male (Oaxaca–Blinder I) or population-weighted average (as in Cotton) comes closest to the non-discriminatory wage structure, something that would put estimated discrimination at close to 65%.[15] Conducting decompositions separately for agriculture and

Table 5: Decomposition of Wage Differentials by Caste

	Oaxaca–Blinder I	*Oaxaca–Blinder II*	*Neumark*	*Cotton*
All workers				
Observed wage differences	0.140	0.140	0.140	0.140
Productivity gap	0.127***	0.135	0.113***	0.130***
	(5.94)	(1.48)	(12.63)	(4.16)
Discrimination gap	0.037	0.030	0.051	0.035
	(0.05)	(0.62)	(1.00)	(0.39)
Other caste advantage	n.a.	n.a.	0.021	0.010
			(0.93)	(0.62)
STC disadvantage gap	n.a.	n.a.	0.030	0.025
			(0.39)	(0.05)
Selectivity gap	–0.051	–0.051	–0.051	–0.051
	(0.74)	(0.74)	(0.74)	(0.74)
Agricultural workers only				
Observed wage differences	0.116	0.116	0.116	0.116
Productivity gap	0.087***	0.045	0.080***	0.068
	(2.81)	(1.05)	(7.51)	(2.40)**
Discrimination gap	0.014	0.051	0.011	0.023
	(0.37)	(0.61)	(0.31)	(0.53)
Other caste advantage	n.a.	n.a.	0.001	0.021
			(0.05)	(0.39)
STC disadvantage gap	n.a.	n.a.	0.011	0.002
			(0.32)	(0.15)
Selectivity gap	–0.012	–0.012	–0.012	–0.012
	(0.24)	(0.24)	(0.24)	(0.24)
Non-agricultural workers only				
Observed wage differences	0.094	0.094	0.094	0.094
Productivity gap	0.080***	0.081***	0.078***	0.080***
	(4.89)	(3.87)	(5.26)	(5.07)
Discrimination gap	0.077	0.076	0.079	0.076
	(0.52)	(0.51)	(0.54)	(0.51)
Other caste advantage	n.a.	n.a.	–0.011	0.010
			(–0.42)	(0.36)
STC disadvantage gap	n.a.	n.a.	0.090	0.066
			(0.67)	(0.54)
Selectivity gap	–0.063	–0.063	–0.063	–0.063
	(–0.41)	(–0.41)	(–0.41)	(–0.41)

Note: Figures in parentheses are bootstrapped *t*-statistics based on 500 replications. * significant at 10%; ** significant at 5%; *** significant at 1% level.

non-agriculture suggests that discrimination is consistently higher in the former (with 45% to 68% of the gender gap due to discrimination) as compared to the latter (insignificant estimates).

Disaggregation of the discrimination gap points to higher levels of positive discrimination in favor of males in agriculture where this accounts for 37–47% of the difference versus 12–22% in non-agriculture. Even if it were to leave female labor supply unaffected, discrimination imposes losses of 2.4–3.5% of household income for the landless and 2.2–3.0% for the bottom quartile, 3 to 5 times the benefit a household would receive from participating in India's Public Distribution System (Kochar, 2005).[16]

The estimated wage difference by caste is smaller than for gender and statistically insignificant, consistent with findings from a study focusing on formal employment in India (Jacob, 2006). We note that, with the exception of the Oaxaca–Blinder II estimate, point estimates of productivity gaps in agricultural and non-agricultural sectors are similar across methodologies. At least for informal labor markets, gaps in remuneration that are related to gender are of much greater importance than those due to caste and thus may warrant attention by policymakers.

Level of Income and Discrimination

It is commonly assumed that economic development or opening up of the economy to greater competition will eventually contribute to elimination of gender discrimination (Jarrell and Stanley, 2004). This is in line with decreased discrimination in India after the country's liberalization. In fact, a number of studies find that liberalization led to decreased wage inequality (Mishra and Kumar, 2005) or that trade-related measures had benign influence on the evolution of the industry gender pay gap (Reilly and Dutta, 2005).

While a direct test of this hypothesis would require panel data and is thus left for future research, the fact that our data comes from a diverse set of villages that are characterized by wide variation in per capita income (from Rs 897 to Rs 1,791) provides an opportunity to compare the extent of gender discrimination between high- and low-income villages in each state, respectively.[17] We note that observed wage differences are higher in rich than in poor villages (0.44 versus 0.33), something that is true both for agriculture (0.34 versus 0.30) and non-agriculture (0.44 versus 0.34) although absolute differentials are higher in the latter than the former.

Table 6 reports decomposition results for rich (cols. 1 and 2) and poor villages (cols. 3 and 4). In the aggregate, the discrimination gap is bigger in rich than in poor villages (0.30 versus 0.25), thus rejecting the notion that discrimination will automatically be eliminated with higher levels of economic development. Sectoral disaggregation suggests that this is due to increased levels of discrimination in the agricultural sector where the discrimination gap is 0.34 for rich but only 0.25 or even 0.23 for poor villages. The extent to which labor is able to move out of agriculture is thus likely to be of relevance for the overall trajectory of discrimination.

5. Conclusion

This is one of the few studies to extend the analysis of wage discrimination in India to the informal sector. Results suggest that informal labor markets for rural casual labor—which provide the economic mainstay for the poorest parts of the population—are more severely affected by discrimination than the formal markets that have been traditionally analyzed in the literature. Contrary to the notion that caste would be particularly important in backward rural areas, we cannot reject the evidence of no discrimination by caste; instead all the discrimination in our data is based on gender, concentrated in the agricultural sector. Although gender discrimination is low or non-existent in the non-agricultural sector, there is no evidence to support the belief that it will disappear with development, largely due to its

Table 6: Decomposition of Male and Female Wage Differentials (Rich Villages)

	Rich villages		*Poor villages*	
	Oaxaca–Blinder I	*Cotton*	*Oaxaca–Blinder I*	*Cotton*
All workers				
Observed wage differences	0.434	0.434	0.334	0.334
Productivity gap	0.120***	0.125***	0.136***	0.149***
	(8.72)	(8.29)	(10.47)	(11.46)
Discrimination gap	0.296***	0.292***	0.253***	0.240***
	(5.71)	(4.88)	(5.18)	(4.32)
Male advantage gap		0.092		0.069***
		(3.64)***		(3.00)
Female disadvantage gap		0.200***		0.171***
		(5.70)		(5.18)
Selectivity gap	0.021	0.021	–0.042	–0.042
	(0.43)	(0.43)	(–0.89)	(–0.89)
	0.021	0.021	–0.042	–0.042
Agricultural workers only				
Observed wage differences	0.344	0.344	0.297	0.297
Productivity gap	0.037**	0.040**	0.070***	0.093***
	(2.43)	(2.12)	(4.80)	(6.37)
Discrimination gap	0.338***	0.335***	0.250***	0.227***
	(4.81)	(4.05)	(3.78)	(3.12)
Male advantage gap		0.137		0.080**
		(3.26)***		(2.33)
Female disadvantage gap		0.199***		0.146***
		(4.82)		(3.76)
Selectivity gap	–0.031	–0.031	–0.023	–0.023
	(0.43)	(–0.43)	(–0.34)	(–0.34)
Non-agricultural workers only				
Observed wage differences	0.440	0.440	0.341	0.341
Productivity gap	0.082***	0.090***	0.081***	0.089***
	(2.58)	(2.58)	(3.95)	(3.29)
Discrimination gap	0.211	0.203	0.419	0.412
	(0.67)	(0.62)	(1.35)	(1.26)
Male advantage gap		0.028		0.067
		(0.39)		(0.88)
Female disadvantage gap		0.176		0.345
		(0.69)		(1.37)
Selectivity gap	0.148	0.148	–0.171	–0.171
	(0.57)	(0.57)	(–0.62)	(–0.62)

Note: Figures in parentheses are bootstrapped *t*-statistics based on 500 replications. * significant at 10%; ** significant at 5%; *** significant at 1% level.

prevalence in agriculture. To illustrate the magnitude of these effects, we note that the losses inflicted by gender-related wage discrimination are larger than the benefits provided through programs such as the Public Distribution System on which the government continues to spend very large amounts.

Three policy conclusions stand out. First, the finding that, consistent with evidence from study of the formal sector, the vast majority of wage differences between SCs/STs and other castes can be attributed to differences in pre-existing endowments rather than discrimination per se, implies that the benefits from extending current reservations—to either the private sector or to other backward castes—may be modest. This implies that the ongoing and highly emotional debate on this issue may focus on the wrong issue. Instead, a policy allowing historically disadvantaged groups to build up human and physical capital is likely to be more effective in closing gaps in earnings. Second, the size of gender discrimination found here suggests that it may be useful to complement the emphasis on caste inherent in current policies with a focus on gender. Given the importance of assets as a means to strengthen women's bargaining power (Panda and Agarwal, 2005), finding ways to ensure that reform of inheritance laws, most notably the 2005 change of the Hindu Succession Act, will translate into reality on the ground, will be relevant. Analysis of agricultural production functions rejects the hypothesis of significant differences in productivity between males and females (Deininger et al., 2007). This implies that, especially for females, returns to self-employment are significantly higher than can be obtained in wage labor markets. Expansion of opportunities for women to access productive resources, including land, through means other than ownership, in particular rental, and efforts to expand credit access via self-help groups could thus offer considerable scope to overcome discrimination. Exploring the effectiveness of these policies in general—and their impact on gender discrimination in particular—would be desirable. Availability of panel data would allow expansion in a number of directions by not only accounting for unobserved characteristics at the individual level but also by capturing the dynamics of shifts between sectors. Study of these important issues is left for future research.

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Notes

1. Scheduled castes and tribes, who make up about 15% and 7.5% of India's population, respectively, are members of castes or tribes specifically notified in India's Constitution.

2. Individuals below Hinduism's four main caste (*varna)* groups: *brahmins* (priests, teachers)*, kshatriyas* (warriors, rulers)*, vaishyas/banias* (businessmen or landowners) and *shudras* (laborers, artisans) are often referred to as *dalits* or untouchables. Beyond being confined to menial jobs, beliefs by higher castes that mere contact would defile them led to strict segregation. The concept was officially abolished at independence.

3. Of this difference, 35% is due to an increase in female managers and 10% due to an increase in female workers.

4. Factors taken into account include land ownership, assets, workers education and region.

5. Although our results vary less across methodologies than is reported in some other studies (Neumark, 1988; Oaxaca and Ransom, 1994), they do vary with the underlying assumptions and we therefore report them for all four decomposition methods.

6. Although the sample was part of a panel that had been interviewed in 1971 and 1982 (Foster and Rosenzweig, 2004), the fact that gender-differentiated wage information was not available in the earlier survey prevents us from using data from the earlier rounds for our analysis.

7. Although not reported, all of these differences are statistically significant at the 1% level.

8. Contrary to casual wage work in either the agricultural or non-agricultural sector, salaried work implies a stable job.

9. The corresponding figures are 47% versus 11% for the bottom and top quartile and 45% versus 25% for SC/ST and others.

10. Thus, although non-agricultural employment pays slightly higher wages than agriculture, it also has a larger wage differential.

11. While an increase from 1 to 10 is expected to increase wages by 18%, an increase from 30 to 40 years has, with 3.6% wage increase, a significantly smaller predicted effect.

12. This figure is consistent with the decomposition results reported in the top panel of Table 5 where the discrimination gap between SC/ST and other castes ranges from 0.027 to 0.042 depending on which decomposition method is used.

13. As noted in the tables, the bootstrapping was done for 500 replications each.

14. To exclude the possibility that it is the lower number of female observations in non-agricultural wage employment that is responsible for this result, we randomly chose the corresponding number of observations from the agricultural sample and still obtained a significant coefficient

15. Neumark and Cotton methods allow decomposition of the wage differentials due to discrimination into an element of positive discrimination in favor of males and discrimination against females. Results are reasonably close, with the two methods attributing, respectively, 29% and 33% of the differential to the former and 71% and 67% to the latter.

16. Figures are computed by noting that, as per Table 1, the average landless household spends 285 days of wage labor out of which 27% (or 77 days) is supplied by females. Using wages from

Table 2 implies a wage differential of Rs. 10.09 and Rs. 13.77 for agricultural and non-agricultural work which, multiplied by the number of working days, implies a loss of Rs. 776 or Rs. 1,060, respectively.

17. In view of significant differences in income levels across states, choosing only the top and bottom villages would have made our distinction too similar to a simple regional break-down, something we aim to avoid by choosing high- and low-income villages by state instead. Also, we report the results for Oaxaca–Blinder I and Cotton methods as the assumptions underlying these are most likely the ones present in our data. Results for the other methods are not too different and can be obtained from the authors upon request.