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International Trade and the Gender Wage Gap: New Evidence from India's Manufacturing Sector

NIDHIYA MENON
Brandeis University, Waltham, MA, USA

and

YANA VAN DER MEULEN RODGERS *
Rutgers University, New Brunswick, NJ, USA

Summary. — This study examines how increasing competitive forces from India's trade liberalization have affected women's relative wages and employment. Neoclassical theory implies that costly discrimination against female workers should diminish over time with increased competition. We incorporate this idea into a theoretical model of competition and industry concentration and test the model using repeated cross-sections of India's National Sample Survey Organization (NSSO) household survey data merged with trade and production data from 1983 to 2004. Estimates from ordinary least-squares (OLS) and fixed effects regressions at the industry-level indicate that increasing openness to trade is associated with larger wage gaps in India's concentrated manufacturing industries.

Key words — trade liberalization, gender wage gap, India, discrimination, Asia, competition

1. INTRODUCTION

Precipitated by a balance of payments crisis, India has adopted several waves of far-reaching trade reforms since 1991. The reforms have included sharp reductions in the number of goods subject to licensing and other non-tariff barriers, reductions in export restrictions, and tariff cuts across all industries. These changes raise an interesting question as to how the new wave of competitive forces and the growing pressure for employers to cut costs have affected the wages of male and female workers in India's manufacturing sector. With less government protection and with increased exposure to competition from abroad, employment and pay patterns in manufacturing changed markedly following the liberalization. Yet manufacturing industries experienced quite a bit of variation in the timing and extent of tariff cuts during and after the 1991 reforms. These differential rates in trade liberalization across industries provide an excellent opportunity for examining the impact of increasing exposure to international trade on gender wage differentials.

Neoclassical theory of labor market discrimination implies that increased competition from international trade will reduce the wage gap. In a market economy where discrimination is costly, employers are less able to discriminate against women as competitive forces drive down profit margins (Becker, 1971). We incorporate this idea into a theoretical model of competition and industry concentration in which the impact of international trade on the gender wage gap depends on changes in market characteristics and a parameter which represents the wage premium paid to male workers. Our theoretical model introduces elements of discriminatory firm behavior into a competitive market framework to show that the implied outcome of a reduction in the wage gap does not necessarily hold. We then test the theory by estimating the impact of the trade reforms on gender wage differentials using five cross-sections of household survey data from the National Sample Survey Organization (NSSO) during 1983–2004. We aggregate these data to the industry-level and merge the data with several other industry-level data sets for international trade, output, and industry structure.

The empirics examine the relationship between the male–female residual wage gap and variations across time and industry in exposure to international trade competition. Our strategy centers on comparing the effects of international trade in India's more-concentrated manufacturing industries, where firms enjoyed rents and could afford the costs associated with discrimination, with trade effects in India's less-concentrated manufacturing industries, where firms experienced greater domestic competition and were less able to discriminate. Following Black and Brainerd (2004), this strategy is adopted since the aim here is to measure the effect of increased international trade (resulting from trade liberalization) on the gender wage gap. Industries in the less-concentrated (competitive) sector are subject to competition from other industries in the same sector, and are perhaps also subject to competition from overseas as a consequence of increased openness to trade. Suppose there was an increase in the gender wage gap in the less-concentrated sector. Because industries in this sector are exposed to other forces in addition to those of increased international trade, it would not be clear what part of the increase in the gender wage gap was due to trade liberalization and

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what part was due to competition from domestic forces. Since industries in the concentrated sector are relatively insulated from domestic competition, any change in the gender pay differential in this sector could be attributed more unambiguously to international trade. Thus as in Black and Brainerd (2004), we adopt a difference-in-difference-in-difference approach (which exploits sources of variation across time, industry-level domestic concentration, and industry-level openness to trade) to measure the effect of international trade on the gender wage gap, where industries in the less-concentrated sector are used as a control for changes in the relative pay differential that may not be due to increased exposure to trade (e.g., changes in the educational attainment or labor force attachment of female workers).

The impact of increased competitiveness from international trade on women's relative pay remains an empirical issue. Relatively few studies have gone beyond descriptive analyzes of changes in women's relative wages in the periods of increasing trade openness and growing competition. [1] The limited number of studies that do employ econometric techniques to identify the impact of competition and international trade on the gender wage gaps have found conflicting results. In particular, Hellerstein, Neumark, and Troske (2002) find little evidence that more discriminatory employers with market power are punished over time through buy-outs or lower growth. Berik, Rodgers, and Zveglich (2004) find evidence that increasing trade openness is associated with higher residual wage gaps between men and women in two East Asian economies, a sign the authors interpret as increased wage discrimination. [2] Yet Black and Brainerd (2004) reach the opposite conclusion for the United States: relatively concentrated manufacturing industries that were exposed to more competition from imports experienced shrinking residual wage gaps. Similarly in Mexico, trade-induced competition in product markets is associated with lower gender earnings differentials (Hazarika & Otero, 2004). Cross-country studies have found mixed evidence. Using data for more than 80 lower- and higher-income economies, Oostendorp (2004) shows that increased trade is associated with reduced wage gaps. However, the opposite result is obtained in the case of skilled workers in lower-income economies.

With our focus on India's extensive trade policy reforms, this study also contributes to a lively debate in the literature on the net social benefits of India's trade liberalization. For example, evidence from a difference-in-difference approach in Topalova (2005) indicates that in districts that were more exposed to trade liberalization, both the incidence and depth of poverty decreased by less than the reductions observed in other districts that had fewer industries exposed to trade liberalization. India's trade liberalization also appears to have had negative impacts on child well-being. Findings in Edmonds, Pavcnik, and Topalova (2005) suggest that adjustment costs associated with trade liberalization were responsible for smaller declines in child labor and smaller improvements in school attendance in districts exposed to tariff cuts, compared to districts less exposed to the tariff reductions. [3] Trade liberalization also had differential effects on male and female employment in India. According to Bhaumik (2003), the growth in the workforce share classified as casual accelerated after 1993 as a result of the economic liberalization policies, with larger increases for female workers compared to their male counterparts in both rural and urban areas. Unskilled workers also did not fare well under trade liberalization, with findings in Dutta (2007) showing that tariff cuts had an adverse effect on the relative wages of unskilled workers and on overall wage inequality. Furthermore, disparities in the material standard of living have persisted among Indian women of different castes during the early years of economic liberalization, despite the improvements in educational attainment (Deshpande, 2007).

However, not all studies have found negative social impacts for India. In particular, Chamarbagwala (2006) examines labor market supply and demand shifts associated with India's trade liberalization and domestic economic reforms and finds that skill up-grading within India's industries led to large demand increases for skilled labor and the creation of new white collar jobs, especially in the service sector. [4] Moreover, rapid economic growth in the 1990s following India's liberalization is associated with improvements in short-term and longer-term indicators of children's nutritional status, especially for boys (Tarozzi & Mahajan, 2007). In addition to this debate, we ask how the competitive market forces associated with India's trade policy reforms may have affected discriminatory pay practices in the manufacturing sector. We find that increasing openness to trade is associated with a widening in the wage gap in India's concentrated manufacturing industries.

2. THEORETICAL MODEL: TRADE COMPETITION, MARKET POWER, AND DISCRIMINATION

In a neoclassical framework, discrimination is costly to employers and will not persist in a competitive market environment (Becker, 1971). This hypothesis can be restated in an open economy context, whereby firms operating in industries that face international competition will experience greater pressure to cut costs, including costs associated with discrimination. In the longer-term, discrimination is then expected to lessen in industries that are more open to trade. One can hypothesize that firms in concentrated industries face less competition from other domestic firms, and therefore experience less domestic pressure to cut costs (Borjas & Ramey, 1995). If discrimination is costly, then we would expect any observed reduction in wage discrimination against female workers in concentrated industries to be caused by the competitive forces from international trade rather than other domestic firms (Black & Brainerd, 2004). In the exposition that follows, Borjas and Ramey (1995), which, in turn, is based on Abowd and Lemieux (1991), is used as the foundation to obtain an expression for equilibrium wages received by the workers employed in the concentrated sector. We then model the distribution of equilibrium wages between male and female employees in the concentrated sector by building on Becker (1971).

Before discussing the mechanics of the model, it is useful to provide a brief description of what the model accomplishes. Neoclassical theory based on Becker (1971) implies that an increase in competition associated with trade should reduce the male–female wage gap. Non-neoclassical theory, as developed in Darity and Williams (1985) and Williams (1987), implies that an increase in trade can actually increase gender wage gaps in countries where female workers may have lower bargaining power and where women are segregated into lower-paying, lower-status jobs. The model we develop below is a combination of these effects.

Following Abowd and Lemieux (1991) and Borjas and Ramey (1995), the domestic economy consists of two sectors: the competitive sector (sector 0) and the concentrated sector (sector 1). The competitive sector produces a consumption good y_0, and the concentrated sector produces a consumption good y_1. In other sections of our study, we refer to the competitive sector as the less-concentrated sector. Development of the competitive sector follows Borjas and Ramey (1995), and is not discussed in detail here. Similar to their formulation of the concentrated sector, sector 1 in our study is composed of n firms, each of whom behaves as a Cournot oligopolist. We begin by considering an inverse demand curve that relates price of good y_1 relative to price of $y_0(p_1)$ to the total demand for good y_1.[5] This inverse demand curve is

$$p_1 = \beta_0 - \beta_1 y_1, \quad \beta_0, \beta_1 > 0. \tag{1}$$

Total output of the concentrated sector in the domestic economy (y_1) is composed of the sum of the output of firm i, y_{1i}, the output of the other $(n-1)$ firms each of whom produces y_1', and v, which is the volume of net trade in good 1. Like Borjas and Ramey (1995), we assume that v is exogenous. This is necessary to ensure an unbiased measure of the effect of trade on relative gender pay differentials. Re-writing (1), the inverse demand curve now is

$$p_1 = \beta_0 - \beta_1(y_{1i} + (n-1)y_1' + v). \tag{2}$$

Next, suppose that L_{1i} is the total number of workers employed by firm i in the concentrated sector. Using the Borjas and Ramey (1995) production function as a basis, assume that the production of y_{1i} is directly proportional to L_{1i}. Also assume that firm i and a union with which it is associated jointly maximize rents in a Nash bargaining framework, and that the union receives a proportion λ of the equilibrium level of rents to distribute among workers. Where ω_0 is wage in the competitive sector (we assume that there is no differential between male and female wages in the competitive sector), the expression for rents for firm i is given by

$$p_1 y_{1i} - \omega_0(1+d)L_{1i}, \tag{3}$$

where $\omega_0(1+d)$ is interpreted as a general expression for wages in the concentrated sector. Here d is a parameter which introduces a difference between the wages of the competitive and concentrated sectors; as explained below in Eqn. (8), this difference arises from the relatively higher wage at which male employees are hired in the concentrated sector.

Maximizing (3) with respect to the optimal level of production of y_{1i}, we can show that in a symmetric equilibrium[6]

$$y_{1i}^* = \frac{\beta_0 - \omega_0(1+d) - \beta_1 v}{\beta_1(n+1)}. \tag{4}$$

Given the rent maximizing level of output in (4), we can derive an expression for the equilibrium rents of firm i and its workers using (3). This is as below

$$\text{Rents}_i^* = \frac{(\beta_0 - \omega_0(1+d) - \beta_1 v)^2}{\beta_1(n+1)^2}. \tag{5}$$

Using (5) and the fact that rents to the workforce in the concentrated sector equals λ proportion of equilibrium rents (i.e., $(\omega_1 - \omega_0)L_{1i} = \lambda \text{Rents}_i^*$), equilibrium wages for workers in the concentrated sector ω_1^* are

$$\omega_1^* = \omega_0 + \lambda \frac{(\beta_0 - \omega_0(1+d) - \beta_1 v)}{(n+1)}. \tag{6}$$

Eqn. (6) highlights two things—the first is that wages in the concentrated sector differ from the wages in the competitive sector by a mark-up which is often positive. This is the case in the five years of NSSO data that we consider, where the average real wage of workers in the concentrated sector is higher than that of workers in the less-concentrated sector. The second point is that since average real wages in the concentrated sector are higher, women may still want to be employed there despite receiving relatively lower pay.

Next, we model the distribution of wages between male and female workers in the concentrated sector. To derive a measure for the gender wage gap in this sector, we postulate that the equilibrium wage in (6) is the weighted average of the wages paid to male and female workers, where weights are the shares of male and female workers. That is

$$\omega_1^* = s^m \omega_1^m + (1 - s^m)\omega_1^f, \tag{7}$$

where s^m is the share of males among all workers in the concentrated sector, ω_1^m represents wages to males, and ω_1^f represents wages to females in this sector. From Becker (1971), a wage gap exists in the concentrated sector as the male workers are employed by firm i at a relatively higher wage, as follows:

$$\omega_1^m = \omega_1^f(1+d), \tag{8}$$

where d is the parameter that represents the wage premium for male employees in the concentrated sector.[7] Deriving an expression for ω_1^* in terms of the female wage ω_1^f (using (8)) and substituting this in (7), we can show that

$$\begin{aligned}\omega_1^{m^*} &= \frac{(1+d)}{(1+ds^m)}\left(\omega_0 + \lambda \frac{(\beta_0 - \omega_0(1+d) - \beta_1 v)}{n+1}\right) \\ &= \frac{(1+d)}{(1+ds^m)}\omega_1^*\end{aligned} \tag{9}$$

and

$$\begin{aligned}\omega_1^{f^*} &= \frac{1}{(1+ds^m)}\left(\omega_0 + \lambda \frac{(\beta_0 - \omega_0(1+d) - \beta_1 v)}{n+1}\right) \\ &= \frac{1}{(1+ds^m)}\omega_1^*.\end{aligned} \tag{10}$$

What determines d? In the context of our study, we formulate that d is positively influenced by the exogenous net trade in good 1, measured by v. Why might d increase with v? Plausible reasons include the fact that with trade, rents in the concentrated sector fall. This assertion is supported by the evidence in Krishna and Mitra (1998) showing that trade liberalization has resulted in higher levels of competition within the Indian economy, as measured by reductions in price mark-ups over marginal cost. If firms in the concentrated sector discriminate against women, they may want to maintain male wages at the expense of female wages. With smaller rents, this means that female wages fall more, that is, d increases.

An increase in d with trade is also consistent with the theoretical model developed in Rosen (2003). Rosen extends the Becker argument in a framework that includes search frictions in the labor market as well as wages set by bargaining. The discrimination coefficient is a firm-specific disutility associated with hiring female workers, and this coefficient affects firm profits through wages and hiring. Although discriminatory firms employ male and female workers, firms with high discrimination coefficients are more selective in their hiring decisions for female workers than for male workers, causing them to hire fewer than the optimal number of female workers. At the same time, discriminatory firms pay their female workers relatively low-wages, which contributes to a total wage bill that is less than the wage bill of non-discriminatory firms. Because the positive profit impact from a lower wage bill dominates the negative profit impact from the suboptimal hiring decisions, discriminatory firms are more profitable. In this framework, competitive market forces drive out non-discriminatory firms instead of discriminatory firms. Placing our study in the context of Rosen (2003), the average value of d (across firms) may rise with international trade since firms with lower

d are less profitable and so exit the market. We model the positive link between d and v as

$$d = \alpha_0 + \alpha_1 v; \quad \alpha_1 > 0. \tag{11}$$

Note that (11) implies that v determines d, which, in turn, influences equilibrium male and female wages in the concentrated sector as in Eqns. (9) and (10). Econometrically, Eqn. (11) may be thought of as a reduced form equation.

We conclude our theory by defining ψ, the relative difference between male and female wages in the concentrated sector. Thus

$$\psi = \frac{\omega_1^{m^*} - \omega_1^{f^*}}{\omega_1^{m^*}} = 1 - \frac{\omega_1^{f^*}}{\omega_1^{m^*}}. \tag{12}$$

Substituting from (9)–(11) above

$$\psi = \frac{d}{(1+d)} = \frac{(\alpha_0 + \alpha_1 v)}{(1 + \alpha_0 + \alpha_1 v)}. \tag{13}$$

So ψ, the gender wage differential in the concentrated sector, is a function of the parameter d. To study the effect of an increase in trade on the gender wage differential in the concentrated sector, we are interested in the following derivative of (13)

$$\frac{\partial \psi}{\partial v} = \frac{\alpha_1}{(1 + \alpha_0 + \alpha_1 v)^2} > 0. \tag{14}$$

From (14), the relative pay differential in the concentrated sector increases with trade. These theoretical implications are tested in the empirics that follow.

3. DATA DESCRIPTION

To explore the labor market impacts of trade policy reforms, we use five cross-sections of household survey data collected by the NSSO. The data include the years 1983 (38th round), 1987–88 (43rd round), 1993–94 (50th round), 1999–2000 (55th round), and 2004 (60th round), providing us with data coverage before, during, and after the trade liberalization. For each round, we utilize the employment and unemployment module—Household Schedule 10. To construct our labor force sample, we retain all regular wage employees of prime working-age (ages 15–60) with positive weekly cash wages in the manufacturing sector.[8] All employment and wage variables are aggregated to the industry-level using India's National Industrial Classification (NIC) system, which is based on international standards. The two earlier rounds of NSSO data use the 1970 NIC codes, the 50th round uses the 1987 NIC codes, and the two later rounds of NSSO data use the 1998 NIC codes. There are major differences at all levels of disaggregation beyond the one-digit level between these NIC codes; these are incorporated in our empirical analysis.

Data on export and import values across manufacturing industries, from 1980 to 2004, are constructed using the World Bank's Trade, Production and Protection Database (Nicita & Olarreaga, 2006). We construct three measures of industry-level trade openness: exports/output, imports/output, and (exports + imports)/output. Comprehensive data sources on trade policies are less readily available compared to trade values; the data we located in the World Bank's Trade, Production and Protection Database only covered the years 1990, 1992, 1997, 1999, 2001, and 2004. These data took the form of industry-level tariff rates for 28 manufacturing sectors, constructed as simple averages of tariffs applied on goods entering the country. In an effort to construct tariff series for the earlier years, we used tariff data by industry for the years 1983 and 1989 published in Gang and Pandey (1998a, 1998b) and a concordance table supplied by the authors for consolidating their data into the same 28 manufacturing categories as the World Bank's series. Although both tariff rates and trade shares are appropriate for an empirical test that focuses on industry-level competition, the empirical analysis focuses mostly on trade shares because the tariff data are plagued with missing values. We do run a series of specification tests using the tariff series and report the results in the robustness section.

Data on output across manufacturing industries are obtained from India's Annual Survey of Industries (ASI).[9] Because the domestic output data are in rupees and the trade series are in dollars, we use average annual rupee/US$ exchange rates to convert output into dollars. The ASI data are used to construct an index of domestic concentration across manufacturing industries. This index is based on the number of enterprises relative to output, by industry. All our data sources are summarized in Appendix 1. As with the household data, various years of ASI data are classified according to the different versions of India's NIC classification system: the 1970 NIC codes are used up to and including ASI 1988–89, the 1987 NIC codes are used from ASI 1989–90 to ASI 1997–98, the 1998 NIC codes are used from ASI 1998–99 to ASI 2003–04, and the 2004 NIC codes are used for ASI 2004–05.

Because tests of the theoretical model are conducted at the industry-level, all data series are aggregated to the same sets of industries using consistent industry codes. We adopted the same categorization as the World Bank Trade, Production and Protection series, which uses the ISIC (Revision 2) classification at the three digit level and contains 28 industry categories per year. The NSSO labor data and the ASI production data are converted to this classification scheme using the concordance schedule we created based on the information in Central Statistical Organization (1970, 1987, 1998, 2004), Sivadasan and Slemrod (2006). The concordance schedule is reported in Appendix 2. To the best of our knowledge, this table is the only source for concordance matching between the ISIC classification and five waves of NIC classifications, from 1970 to 2004.

4. DESCRIPTIVE ANALYSIS: TRADE LIBERALIZATION AND GENDER WAGE DIFFERENTIALS

Like many developing countries in the post-WWII era, India based its economic development and trade policies on an import substitution strategy. The country had some of the highest tariff rates and most restrictive non-tariff barriers in the region (Krishna & Mitra, 1998; Topalova, 2005). Yet in 1990 and early 1991, a series of external, political, and macroeconomic shocks—including an oil price hike spurred by the Gulf War, a reduction in remittances from Indians employed in the Middle East, a shake-up in investor confidence following the assassination of Rajiv Gandhi, and growing fiscal and trade deficits—precipitated a financial crisis (Edmonds *et al.*, 2005). The Indian government requested stand-by assistance from the International Monetary Fund in August 1991, and in return, agreed to what had become a fairly standard policy prescription of stabilization and structural adjustment policies. Strong internal pressure from the business community and a growing entrepreneurial class also contributed to the impetus for economic reform (Pedersen, 2000). The government aimed to reduce tariff levels on a wide range of imported products, lower the variation across sectors in tariff rates, simplify the tariff structure, and remove many of the exemptions (Krishna & Mitra, 1998; Topalova, 2005). Several new waves of reforms occurred in 1994 and 1997, with a slowdown in the pace of trade liberalization after 1997 as pressures from international agencies and creditors subsided.

Manufacturing industries across the board experienced some degree of tariff reductions during and after the initial sweeping 1991 reform package, and India's imports and exports grew dramatically as a result. Figure 1, which reports trends in exports and imports as a share of production, shows that both the aggregate export share and import share jumped sharply after 1991 and continued to rise steadily until the late 1990s. With a slowdown in the pace of trade liberalization, the growth in trade ratios eased during the early 2000s, especially for imports. Superimposed onto this diagram are residual wage gaps found by the Oaxaca–Blinder decomposition procedure with results suggesting that in the midst of India's comprehensive trade liberalization, the residual wage gap between men and women increased.

The Oaxaca–Blinder procedure helps to understand the extent to which the overall wage gap can be explained by observed productivity characteristics between men and women (Blinder 1973; Oaxaca 1973). This procedure decomposes the wage gap in a particular year into a portion explained by average group differences in productivity characteristics and a residual portion that is commonly attributed to discrimination. For a given cross-section, one decomposes the gender wage gap by expressing the natural logarithm of real wages (w) for male workers ($i = m$) and female workers ($i = f$) as follows:

$$w_i = X_i\beta_i + \varepsilon_i. \tag{15}$$

The notation X denotes a set of worker characteristics that affect wages. Within X, we use a set of dummy variables for education level attained; an indicator variable for whether the individual has any technical education; years of potential experience and its square; interaction terms for education level and years of potential experience; number of pre-school children in the household; and binary variables for regional location, rural status, marital status, low-caste status, self-employed status, religion, and household headship.[10] Most of these variables, including the number of pre-school children, marital status, and household headship, are fairly standard control variables in wage regressions across countries. The interaction between education and potential experience allows for changes in the education coefficients as employers become better informed about their workers over time (Altonji & Pierret, 2001). The location dummy variables control for regional differences in laws and regulations in India (Besley & Burgess, 2004). In India, wages can be lower for individuals belonging to castes that are perceived as inferior and for individuals who are not Hindu (Bhaumik & Chakrabarty, 2007). The notation ε is a random error term assumed to be normally distributed with variance σ^2. One can then describe the gender gap as follows:

$$w_m - w_f = (X_m\beta_m - X_f\beta_f) + (\varepsilon_m - \varepsilon_f). \tag{16}$$

If one evaluates the regressions at the means of the log-wage distributions, the last term becomes zero. Adding and subtracting $X_f\beta_m$ to obtain worker attributes in terms of "male prices" gives

$$w_m - w_f = (X_m - X_f)\beta_m + X_f(\beta_m - \beta_f) + (\varepsilon_m - \varepsilon_f). \tag{17}$$

The left-hand side of Eqn. (17) is the total log-wage differential. On the right-hand side, the first term is the explained gap (the portion of the gap attributed to gender differences in measured productivity characteristics) and the second term is the residual gap (the portion attributed to gender differences in market returns to those characteristics). The remaining term is generally ignored as the decomposition is usually conducted at the means; otherwise, the sum of the last two terms is considered the residual gap.

In performing the decomposition, the convention in the literature is to use the male coefficients since it is presumed that male wages better reflect the market payoffs for productivity characteristics. Appendix 3 reports the sample means and standard deviations for men and women in 1983 and 2004, and Appendix 4 shows the male coefficients estimated from

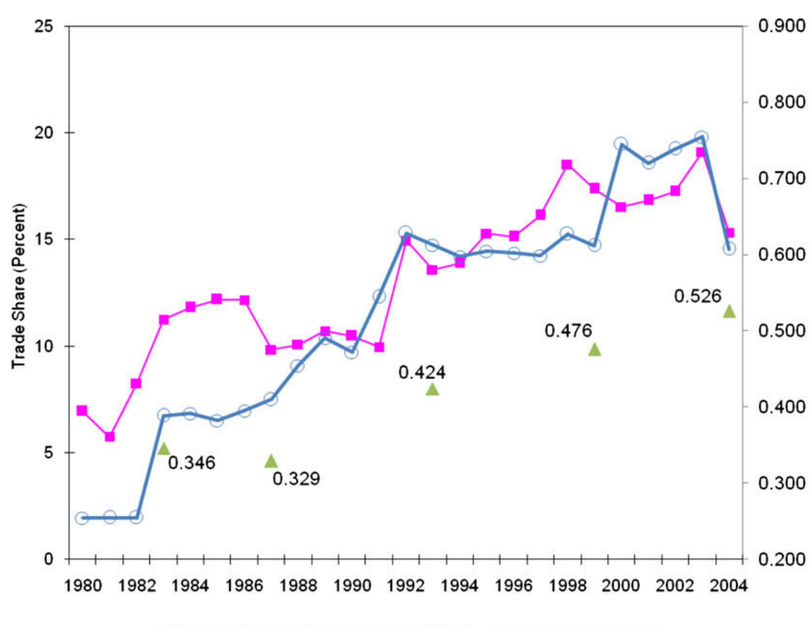

Figure 1. *Trade ratios and male–female residual wage gap, 1980–2004. Source: Authors' calculations based on data sources in Appendix 1.*

wage regressions in each year. These regressions are weighted using sample weights provided in the NSSO data for the relevant years; the weights correct for the fact that the proportion of individuals and households in each sample differs from the proportion in the true population. Use of these weights thus adjusts the coefficients to make them nationally representative.[11] In Appendix 4, the excluded education level is no schooling (illiterate), and the excluded regional dummy relates to states in the western region of India. As evident, general education, technical education and experience have positive effects on wages in most years. Wages are lower for self-employed individuals, for individuals belonging to castes that are perceived as inferior, and, in some years, for individuals employed in the rural areas of India. Furthermore, on average, wages appear to be consistently lower in the southern regions as compared to other locations in India. The male wage regression coefficients are then applied to female worker characteristics to construct measures of the residual wage gap.[12]

Results from the Oaxaca–Blinder decomposition are reported in Table 1. The table shows that in 1983, the total male–female wage gap in log points stood at 0.612. This gap can be converted to a ratio of geometric means by exponentiating its negative, yielding a female to male wage ratio of just 54.2%. The total wage gap fluctuated somewhat over time, ending with a wider gap of 0.677 log points in 2004. This end point is equivalent to a relative female wage of 50.8%, which is extremely low by international standards. Table 1 also shows that in all years, more than half of the total gender wage gap in India remains unexplained by education, experience, and other human capital characteristics. In 1983, 56.5% of the wage gap remained unexplained; this portion grew to 77.7% by 2004. During the late 1980s and early 1990s, the explained wage gap actually increased, a result that is consistent with the findings in Kijima (2006) of a widening in the overall distribution of observed skills during that period. After 1993–94, the explained gap steadily fell as women gained relatively more education and experience.

Working against this improvement was a steady widening in the residual gap between men and women for most of the period. This widening in the gap could be explained by the growing dispersion in returns to observed skills (as argued in Kijima (2006)), growing importance of unobserved skills, or by rising discrimination. To further explore this issue, we conducted a more detailed decomposition procedure that follows the approach in Juhn, Murphy, and Pierce (1991).[13] Findings indicate that unmeasured gender-specific factors (which could include unobserved skills as well as discrimination) have become more important determinants of gender wage differentials, especially after 1987. Results show on average, changes in unobserved gender-specific characteristics caused the wage gap to widen by 2.8% per year during 1987–2004. Also contributing to wider wage gaps is the growing dispersion in the returns to education and returns to other observed skills, which caused the total wage gap between men and women to widen by 1.1% per year during this period. These changes have offset female gains due to education and observed productivity characteristics.

Table 1. *Oaxaca–Blinder decomposition results for male–female wage gap (in log points)*

	1983	1987–88	1993–94	1999–2000	2004
Total M–F wage gap	0.612	0.616	0.765	0.757	0.677
Explained	0.266	0.287	0.341	0.281	0.151
Unexplained (residual)	0.346	0.329	0.424	0.476	0.526
% Gap unexplained	56.5%	53.4%	55.4%	62.9%	77.7%

Note: The total wage gap is male wages–female wages; the explained wage gap is gender differences in observed characteristics weighted by male coefficients; and the residual wage gap is the portion that cannot be explained by the differences in characteristics. All results are in log points except bottom row, which is in percentage points.

The steadily increasing trend in the residual wage gap is evident in Figure 1, which shows that the period of rising trade openness in the 1990s coincided with an increase in the residual pay differential between men and women. This descriptive analysis suggests that growing competition from greater exposure to world markets is associated with downward pressure on women's relative pay.

Individual firms in India faced competition not only from abroad but also from other domestic firms in the same industry. One way to measure domestic competition is firm concentration, which is often measured by the four-firm concentration ratio or the Herfindahl Index. To construct these measures, we would need information on either the output or the value of sales of each firm in each of the industries that we consider across the 1983–2004 period. Because such data are not readily available, we turned to a widely used proxy for concentration based on the number of industry-specific establishments divided by an industry-specific measure of scale.[14] We construct the index of domestic concentration as (1 − #establishments/output), so that the higher values correspond with a greater concentration (i.e., fewer establishments), with the intuition that changes in this measure indicate changes in the representative firm's share of the market in that industry (Sen & Chand, 1999). Although the data to construct this measure are available, a drawback is that the measure does not control for differences in the capital intensity of production across industries. The average index from 1980 to 2004 is reported in Table 2, with industries ranked from the most to least concentrated. Results indicate that petroleum refinery, industrial chemicals, and iron and steel rank are the most concentrated industries in India, while wood products, furniture, tobacco, and pottery rank are the least concentrated industries. For purposes of the descriptive analysis, we grouped industries into two groups, "more-concentrated" and "less-concentrated," by choosing a natural break point (based on the size of the marginal decreases in the concentration numbers in moving from more- to less-concentrated) approximately in the middle of the concentration series. For the subsequent regression analysis, we specify a richer measure of concentration in its continuous form rather than a dummy variable.

To better understand changing trade patterns across industries, we used the "more-concentrated" and "less-concentrated" groupings to construct average export ratios and average import ratios according to these classifications. As shown in Figure 2, industries that experienced more domestic competition (i.e., the less-concentrated group) also opened more to international trade after the reforms. Both imports/output and exports/output in less-concentrated industries grew more than the corresponding trade ratios in more-concentrated industries. The figure also shows that imports dominate exports in more-concentrated industries, while exports dominate imports in less-concentrated industries.

Although trade activity differs considerably across these two classifications of industries, both groups experienced substantial cuts in tariff rates. We used the available data on average tariffs by industry and further averaged these industry-level aggregates (using employment shares as weights) into two series, for more- and less-concentrated industries. As shown in Figure 2, tariff rates have fallen drastically since 1983 across

Table 2. *Index of domestic concentration, 1980–2004*

ISIC	Industry label	(1 − No. establishments/ output)
More-concentrated		
353	Petroleum refinery	0.999
351	Industrial chemicals	0.978
371	Iron and steel	0.968
354	Miscellaneous petroleum and coal products	0.958
384	Transport equipment	0.955
313	Beverages	0.943
383	Machinery (electric)	0.940
352	Other chemicals	0.938
355	Rubber products	0.920
372	Non-ferrous metals	0.919
324	Footwear (except rubber or plastic)	0.913
321	Textiles	0.909
341	Paper and products	0.906
311	Food products	0.893
382	Machinery (except electrical)	0.888
Less-concentrated		
362	Glass and products	0.876
323	Leather products	0.869
385	Professional and scientific equipment	0.864
322	Wearing apparel (except footwear)	0.850
356	Plastic products	0.829
390	Other manufactured products	0.826
369	Other non-metallic mineral products	0.791
342	Printing and publishing	0.764
381	Fabricated metal products	0.763
361	Pottery, china, earthenware	0.679
314	Tobacco	0.567
332	Furniture (except metal)	0.295
331	Wood products (except furniture)	0.259

Note: Results show the annual average from 1980–81 to 2004–05 for the industry-specific calculation (1 − no. establishments/output). ISIC codes are from Revision 2.
Source: Authors' calculations based on data sources in Appendix 1.

industries. On average, the cuts were slightly bigger in more-concentrated industries, falling by 85.5 percentage points from 115.6% in 1983 to 30.1% in 2004. In less-concentrated industries, average tariff rates fell by 84.0 percentage points, from 112.6% to 28.6% in the same period. Within these aggregate measures, the tariff data indicate that the beverages industry (a more-concentrated industry) stands out for exceptionally high tariffs that took a relatively long time to be reduced, while most other industries went through drastic tariff cuts during the reform period. Petroleum and food products (both more-concentrated) and plastic products and tobacco (both less-concentrated) saw particularly large reductions in tariff rates.

According to the implications of the Becker theory, one would expect the share of female employment to rise in more-concentrated industries after trade liberalization, as the squeeze on profits would induce firms to hire more of the relatively cheaper source of female labor. The descriptive evidence in Table 3 on employment distributions and the female share of the regular salaried workforce provides some support of this hypothesis. As reported at the bottom of the table, women's representation in the manufacturing sector's regular salaried labor force has increased from 7.6% in 1983 to 14.0% in 2004. Within manufacturing, India's employment distribution resembles that of many developing countries, with relatively high female representation in low-skilled labor intensive industries such as apparel, pottery, glass products, and tobacco, and relatively high male representation in higher skilled labor and capital intensive industries such as petroleum refinery, paper and products, non-ferrous metals, fabricated metal products, and machinery.

Between 1983 (pre-liberalization) and 2004 (post-liberalization), most industries in the more-concentrated and less-concentrated groupings experienced an increase in women's representation in the workforce, coinciding with the feminization of the manufacturing sector workforce. For example, electric machinery saw an increase in the female share of its regular salaried workforce from 4.6% to 19.5%, and wearing apparel experienced an increase from 16.1% to 23.1%. One of the most noticeable changes in the male employment distribution was a movement out of textiles, a more-concentrated industry, into a variety of less-concentrated industries. In the female employment distribution, a very large shift out of the tobacco industry is one of the forces behind women's increased employment in other industries. When we construct weighted averages for the more- and less-concentrated groups, we find that during 1983–2004, the gain in average percent female for more-concentrated industries exceeded the gain for less-concentrated industries.

5. TESTING THE THEORETICAL MODEL WITH INDUSTRY-LEVEL REGRESSIONS

Next, we perform industry-level regressions to test the theoretical model of foreign trade competition, market power, and discrimination. Consistent with the model's specification of a sector that is competitive domestically (sector 0) and a sector that is concentrated (sector 1), our estimation strategy is grounded in a comparison by concentration status. The estimation also builds on the idea that international trade works through different channels, including the discrimination coefficient, to affect the gender wage differential. Underlying the empirical tests is a difference-in-difference-in-difference strategy, modeled after Black and Brainerd (2004), which uses residual wage gaps between men and women as the proxy for discrimination. The approach effectively entails taking the difference in the residual wage gaps between more-concentrated industries that were relatively open and closed to trade, and subtracting from this total the difference in residual wage gaps between less-concentrated industries that were relatively open and closed to trade.

This approach can be implemented with alternative methods that vary in treatment of the underlying dynamics over time. One approach, as employed in Black and Brainerd (2004), applies ordinary least-squares (OLS) to a cross-section of long-differenced data. Their reasoning involves controlling for differing changes in women's unobserved characteristics across trade-affected industries and more-concentrated industries that may help to explain some of the observed changes in women's relative wages across industries. Examples of changes in unobserved characteristics include increases in women's commitment to the labor force as they wait longer to have children, or changes in women's relative productivity that are not measured by education and experience. While the simplicity of applying OLS to cross-sectional data is appealing, its restriction to data that is long-differenced between an end year and the beginning year may be inadequate in capturing changes in the degree of industry-level competition associated with trade openness. Hence, we adapt the Black and Brainerd approach by using a panel dataset of industry-level observations over time, rather than a cross-section of long-differenced observations. The panel dataset allows for more flexibility in

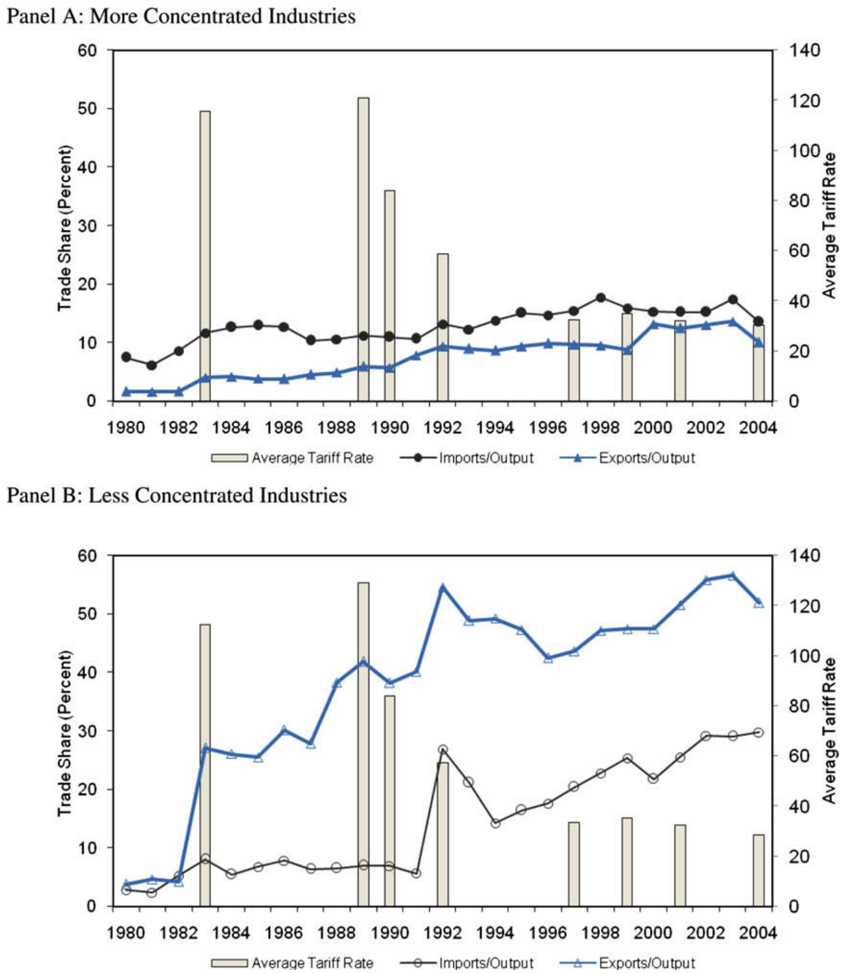

Figure 2. *Average trade ratios and tariff rates by levels of domestic concentration. Note: Industry-level tariffs are the average of tariff rates applied on good entering the country, and average tariffs by concentration are calculated by applying average employment shares to the industry-level tariffs. Source: Authors' calculations based on data sources in Appendix 1.*

modeling movements in wage gaps over time and estimating the effects of trade openness across industries.

Our difference-in-difference-in-difference strategy is represented by the following estimation equation:

$$W_{imt} - W_{ift} = \beta_0 + C_{it}\beta_1 + T_{it}\beta_2 + Y\beta_3 + C_{it}T_{it}\beta_4 + C_{it}Y\beta_5 + T_{it}Y\beta_6 + C_{it}T_{it}Y\beta_7 + \varepsilon_{it}. \tag{18}$$

The notation W_{imt} denotes the total male residual wages in industry i and year t, and W_{ift} denotes the total female residual wages in industry i and year t. The residual wage series for male and female workers, which can be interpreted as the portion of wages that remain unexplained by observed skill characteristics, are constructed following the Oaxaca–Blinder decomposition procedure. These residual wages are then aggregated across industry and year. The notation C_{it} is a continuous variable that measures domestic concentration by industry and year; T_{it} represents competition from international trade and is measured by the share of trade in GDP across industry and year; and Y represents the year, measured in alternative specification tests as either a time trend or a dummy variable that equals one for the post-liberalization years. Note that our use of a year variable to capture the time element differs from Black and Brainerd (2004), who recode their variables as long differences between the end year and the beginning year in order to capture changes over time. Following the intuition in Besley and Burgess (2004), the interaction terms with the year variable may be interpreted as reflecting the time path of trade shares (and domestic concentration). The final term contains the interaction between domestic concentration and international competition and year ($C_{it}T_{it}Y$). We focus on this term's coefficient as it represents the impact of international trade competition in more-concentrated industries over time.

We estimate Eqn. (18) using two alternative methods that varied in the treatment of the underlying dynamics of specific industry effects. In the first approach, we use OLS applied to the panel dataset of industry-level observations over time. All regressions are weighted with industry-level employment shares, and the standard errors are clustered by industry to adjust for intra-group correlation. Results are reported in Table 4 for six different models. The models differ according to the measurement of trade shares and the measurement of the year variable: models 1 and 4 use export shares, models 2 and 5 use import shares, and models 3 and 6 use total trade (exports plus imports) shares. With respect to the year variable, models 1, 2,

Table 3. *Employment distribution and female share of the workforce, by industry (1983–2004)*

	1983			2004		
	Male	Female	% Female	Male	Female	% Female
More-concentrated						
Petroleum refinery	0.1	0.3	14.0	0.8	0.3	5.9
Industrial chemicals	2.9	0.0	0.0	1.7	1.4	12.2
Iron and steel	7.9	3.3	3.3	3.4	2.6	10.9
Misc. petroleum and coal products	0.1	0.0	0.0	0.4	0.2	7.8
Transport equipment	5.8	1.5	2.0	5.7	5.0	12.5
Beverages	0.6	0.2	2.4	0.6	0.8	17.9
Machinery (electric)	5.5	3.2	4.6	2.8	4.1	19.5
Other chemicals	4.8	4.6	7.3	4.1	4.9	16.4
Rubber products	1.1	0.1	0.5	1.5	1.7	15.9
Non-ferrous metals	1.2	0.2	1.6	2.4	0.8	5.2
Footwear (except rubber or plastic)	0.6	0.7	8.7	1.0	0.9	12.6
Textiles	24.5	16.7	5.3	19.9	12.3	9.2
Paper and products	1.5	0.6	3.2	3.9	0.4	1.6
Food products	9.7	5.7	4.5	9.0	8.7	13.7
Machinery (except electrical)	6.2	0.9	1.2	6.2	3.2	7.7
Less-concentrated						
Glass and products	1.1	1.3	9.1	0.7	4.6	53.2
Leather products	0.6	0.8	9.8	0.8	1.1	18.7
Professional and scientific equipment	0.6	0.6	7.4	0.4	0.2	9.3
Wearing apparel (except footwear)	3.2	7.6	16.1	6.3	11.7	23.1
Plastic products	1.1	0.9	6.5	2.8	1.1	6.3
Other manufactured products	3.0	1.8	4.7	4.2	2.2	8.0
Other non-metallic mineral products	3.9	3.5	6.8	3.9	3.1	11.2
Printing and publishing	3.6	3.3	7.0	4.4	4.6	14.6
Fabricated metal products	4.8	1.3	2.2	6.7	3.7	8.4
Pottery china earthenware	0.2	0.6	21.5	0.0	0.3	56.3
Tobacco	2.4	39.7	58.0	2.0	16.2	56.7
Furniture (except metal)	0.6	0.0	0.0	2.1	1.5	10.3
Wood products (except furniture)	2.3	0.6	1.9	2.7	2.1	11.1
All industries total	100.0	100.0	7.6	100.0	100.0	14.0
More-concentrated total	72.7	38.0	4.1	63.2	47.5	10.9
Less-concentrated total	27.3	62.0	15.7	36.8	52.5	18.8

Source: Authors' calculations using population-weighted averages based on NSSO data.

and 3 use a time trend, while models 4, 5, and 6 use a dummy variable for the post-liberalization period.[15]

We begin our discussion of Table 4 by highlighting the positive coefficient estimate on the interaction term for concentration, trade, and year. This result indicates that across most model specifications, increasing trade openness in more-concentrated industries after trade liberalization is associated with higher wage gaps between men and women. The coefficient on this interaction term is positive in all six models, and it is statistically significant in the four models where trade is measured by exports and total trade. Furthermore, the coefficient on the interaction term for trade and year is negative across models and precisely estimated in four of the specifications. This negative coefficient has the interpretation that in the post-liberalization period among less-concentrated industries, the residual wage gap decreased in industries that experienced greater international trade (compared to industries that experienced lower international trade). In the context of our theory, the combination of these two sets of results support the argument that in India, an increase in the volume of trade led to an exacerbation in the wage gap between men and women in concentrated industries. The observed changes in gender pay differentials are likely to have arisen due to pressures from international trade rather than domestic forces since more-concentrated industries experience less domestic competition.

Our second approach to estimating Eqn. (18) is based on a fixed effects strategy to control for time-invariant, industry-specific characteristics that may impact wage gap determinants. These results are found in Table 5, which has a similar structure in terms of how models 1 through 6 are estimated. Regressions are also weighted with industry-level employment shares. As in the case of the OLS results, fixed effects estimates of the coefficient on the key interaction term for concentration, trade, and year are positive. This term is measured with precision in three of the six models we consider. For imports in particular, the introduction of industry dummies appears to absorb some of the variation in the data to reduce the magnitude of the estimated coefficients on the interaction terms of interest. Once we account for industry effects that remain invariant over time, import competition facing Indian firms in manufacturing appears to have a less potent impact on wage gaps compared to the competition in world export markets.

6. INTERPRETATION AND ROBUSTNESS[16]

Implicit in this approach is the assumption that trade shares are an appropriate measure of international competition and are exogenous to the residual wage gap between men and women. Black and Brainerd (2004) cite extensive evidence that

Table 4. *Ordinary least-squares estimates of male–female residual wage gaps by industry (in log points; standard errors in parentheses)*

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Concentration	0.441	0.037	0.945	−0.020	0.149	0.532
	(0.435)	(0.302)	(0.648)	(0.210)	(0.131)	(0.430)
Trade	0.384*	0.130	0.489**	0.124	0.076	0.272
	(0.205)	(0.140)	(0.213)	(0.141)	(0.078)	(0.189)
Year	0.380*	0.023	0.433	1.073**	0.272	1.492*
	(0.204)	(0.201)	(0.322)	(0.548)	(0.414)	(0.904)
Concen × trade	−0.390	−0.289*	−0.614**	−0.108	−0.207**	−0.378
	(0.262)	(0.159)	(0.267)	(0.181)	(0.092)	(0.241)
Concen × year	−0.373*	0.003	−0.446	−1.149*	−0.276	−1.702
	(0.225)	(0.225)	(0.356)	(0.634)	(0.498)	(1.061)
Trade × year	−0.179**	−0.029	−0.190*	−0.430*	−0.137	−0.598*
	(0.088)	(0.096)	(0.111)	(0.221)	(0.253)	(0.336)
Concen × trade × year	0.197**	0.054	0.222*	0.496*	0.214	0.730*
	(0.099)	(0.106)	(0.123)	(0.260)	(0.297)	(0.399)
Constant	−0.328	0.280	−0.587	0.166	0.234**	−0.118
	(0.380)	(0.274)	(0.533)	(0.167)	(0.112)	(0.296)
Number of observations	140	140	140	140	140	140
R^2	0.095	0.202	0.081	0.085	0.186	0.068

Note: The dependent variable across models is the residual wage gap. In Models 1 and 4, trade is exports/output; in Models 2 and 5, trade is imports/output; and in Models 3 and 6, trade is (exports + imports)/output. Also, in Models 1 to 3, year is a time trend; and in Models 4 to 6, year is a post-liberalization dummy. We weighted all regressions with industry-level employment shares, and standard errors are clustered by industry to adjust for intra-industry correlation.
* Denotes statistically significant at 0.10 level.
** Denotes statistically significant at 0.05 level.
*** Denotes statistically significant at 0.01 level.

Table 5. *Fixed effects estimates of male–female residual wage gaps by industry (in log points; standard errors in parentheses)*

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Concentration	0.538	−0.633	0.701	0.531	−0.287	0.454
	(0.532)	(0.465)	(0.565)	(0.551)	(0.417)	(0.590)
Trade	0.630***	0.192	0.606***	0.468**	0.088	0.442**
	(0.208)	(0.177)	(0.214)	(0.216)	(0.139)	(0.212)
Year	0.340	0.040	0.388	0.593	0.223	1.049
	(0.270)	(0.172)	(0.327)	(0.577)	(0.325)	(0.801)
Concen × trade	−0.747***	−0.248	−0.635**	−0.510**	−0.101	−0.398
	(0.246)	(0.197)	(0.248)	(0.249)	(0.153)	(0.246)
Concen × year	−0.328	0.013	−0.417	−0.728	−0.168	−1.318
	(0.281)	(0.187)	(0.335)	(0.669)	(0.383)	(0.943)
Trade × year	−0.190*	−0.026	−0.174	−0.402	−0.093	−0.463
	(0.109)	(0.069)	(0.117)	(0.251)	(0.195)	(0.313)
Concen × trade × year	0.224*	0.038	0.207*	0.526*	0.124	0.590
	(0.116)	(0.071)	(0.121)	(0.296)	(0.221)	(0.367)
Number of observations	140	140	140	140	140	140
R^2	0.718	0.705	0.715	0.706	0.691	0.705

Note: The dependent variable across models is the residual wage gap. In Models 1 and 4, trade is exports/output; in Models 2 and 5, trade is imports/output; and in Models 3 and 6, trade is (exports + imports)/output. Also, in Models 1 to 3, year is a time trend; and in Models 4 to 6, year is a post-liberalization dummy. All regressions are weighted with industry-level employment shares.
* Denotes statistically significant at 0.10 level.
** Denotes statistically significant at 0.05 level.
*** Denotes statistically significant at 0.01 level.

supports the use of trade shares as a measure of competition from international trade. They also suggest a simple test to support the exogeneity assumption: if exogeneity does not hold, then industries with a larger residual wage gap in the beginning year would presumably experience greater trade competition. We conduct a similar test with the Indian data for the relationship between the residual wage gap in 1983 and the change in the import share from 1983 to 2004 and find a correlation coefficient of just 0.23. Although this test is by no means definitive, it provides evidence in support of the exogeneity assumption. As an additional test, we used the tariff data to instrument for the trade shares in both the OLS and the fixed effects regressions using two-stage least-squares. Across the board, the sign on the key interaction term remained positive. For the models with time specified as a trend term, this term lost its precision, and for the models with time specified as a dummy variable for the post-liberalization years, this term was statistically significant. We believe that these additional results provide further statistical evidence in favor of exogeneity of the original trade share series, since the results of the instrumental variables analysis (particularly for the key interaction term) are comparable to the original OLS and fixed effects results.

Another assumption underlying the model and empirical strategy is that before the reforms, wage discrimination was higher in more-concentrated industries *versus* less-concentrated industries. To test the validity of this assumption, we divided industries into more- and less-concentrated categories by specific years, and then constructed employment-weighted averages of the residual wage gaps for both concentration categories using the NSSO data for the two pre-reform years (1983 and 1987–88). Our estimates support our assumption since they indicate that in the pre-reform years, the average residual wage gap is higher in more-concentrated industries (0.204 log points) as compared to less-concentrated industries (0.195 log points).

A well-known drawback to using the residual wage gap is that it serves as a proxy for, rather than a direct measure of, discrimination. Although results in Tables 4 and 5 are consistent with our theoretical argument that changes in the discrimination parameter could outweigh the mitigating effects of trade on the gender pay gap in concentrated industries, the results are also consistent with skill-biased technological change. In particular, industries that are more-concentrated are also more import-oriented (as shown in Figure 2), and in India, more import-oriented industries tend to be more skilled labor intensive and more capital intensive compared to export-oriented industries. Therefore, the demand for skilled labor and the returns to skilled labor will be higher in more import-intensive, concentrated industries.

To examine the extent to which skill-biased technological change occurred in India after trade liberalization, we used the NSSO data to construct a time series measure of skill intensity across industries, and the ASI data to construct a time series measure of capital intensity across industries. We defined skill intensity as the number of workers with college or above, relative to the number of workers with less education, and capital intensity as fixed capital relative to output. Next, we aggregated these series into averages for more- and less-concentrated industries. As shown in Figure 3, both more- and less-concentrated industries showed substantial increases over time in skill and capital intensity. In addition, more-concentrated industries have higher skilled labor intensities in every year, and higher capital intensities in almost every year, relative to less-concentrated industries. To the extent that the residual wage gaps represent gender differences in unobserved skills (with Indian men having higher skill levels than women), the industry-level regression analysis may be capturing the effect of skill-biased technological change on the gender wage gap rather than, or in addition to, changes in the discrimination parameter. These two arguments could be mutually reinforcing. Since Indian men are more likely to hold skilled jobs than women, skill-biased technological change could have led to an increase in firms' preferences to hire skilled men (and hence to an increase in the average d parameter, as argued in Rosen (2003)). This argument is also consistent with the findings in Chamarbagwala (2006) that international trade in manufactured goods favored skilled male workers.

We incorporated skill-biased technological change into the regression analysis by including an industry and time varying measure of skill intensity (the ratio of skilled to unskilled workers as described above) in the OLS models of Table 4 and the fixed effects models of Table 5. We find that upon adding this variable, there is some loss of precision and a decline in magnitude in the key interaction term in both the OLS and fixed effects regressions (three of the six key terms are still significant in both sets of models). However, the skill intensity variable is itself statistically insignificant in all the OLS and fixed effects models. Skill-biased technological change was also incorporated by separately including an industry and time varying measure of capital intensity (ratio of fixed capital to output) in the OLS models of Table 4 and the fixed effects

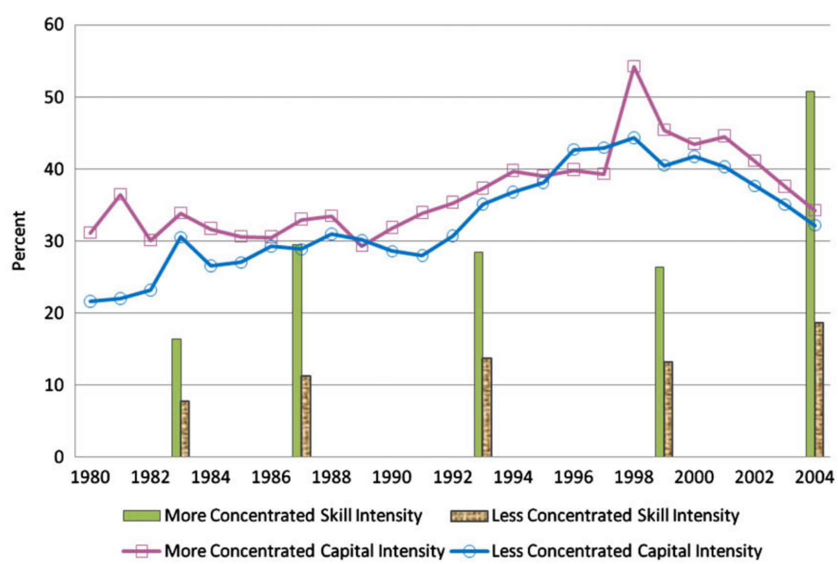

Figure 3. *Skill intensity and capital intensity by levels of domestic concentration, 1980–2004. Note: Skill intensity is constructed as the number of workers with college or above, relative to the number of workers with less education. Capital intensity is constructed as fixed capital relative to output. Source: Authors' calculations based on data sources in Appendix 1.*

of models of Table 5.[17] Again, there is some loss in precision to the key interaction term (three of the six key terms in the OLS models and four of the six key terms in the fixed effects models are significant), but the capital intensity variable itself is measured with an error in all models in which it is included. Variations in the key interaction term upon addition of the skill-biased technological change related variables suggests that following the liberalization of trade rules, such change favored male workers and may help to explain some of the observed increase in the residual wage gap. Finally, since both skill and capital intensity are themselves statistically insignificant in all regression runs, modified versions of Tables 4 and 5 that include these variables are not reported in the manuscript.

Our approach allows the domestic concentration index to vary over time. An argument against this specification is that trade liberalization could have influenced the concentration index, so that the effects of international competition also work through our measure of concentration. One way to address this concern is to keep the competition index as a fixed industry characteristic from the pre-liberalization period. We constructed a new concentration index to reflect the industry-specific average for 1980–90, and fixed this index across year t in the empirical estimation. Results indicate some loss in precision for the export interaction coefficients and some gain in precision for the import interactions coefficients. However, none of the coefficient estimates change sign, so qualitatively our conclusions remain the same.

The results of our empirical models fit into a framework in which groups of workers who have relatively weak bargaining power and lower workplace status may be less able to negotiate for favorable working conditions and higher pay. Thus, women are placed in a vulnerable position as firms compete in the global market place. Our conclusion is supported by the previous studies for India during the 1980s–90s that have found substantial gender wage gaps even after controlling for detailed skill characteristics (Duraisamy & Duraisamy, 1996; Glinskaya & Lokshin, 2007; Kingdon & Unni, 2001). Further outside evidence offers several examples of how female workers may have less bargaining power and limited wage gains as compared to their male counterparts. In particular, a survey of female manufacturing workers in India indicates that women are clustered into low-wage jobs, and when they do hold the same job as men, they are still paid less (South Asian Research & Development Initiative, 1999). This source also reports that women are not as likely as men to receive overtime pay when they work additional hours, and they have inferior access to training and promotion. In addition, union leaders and members are predominately male. Reasons for this include intimidation tactics that make women afraid to join, and union meetings at night when women are engaged in child care. These examples provide some context within which to understand why discrimination might persist or worsen in the case of growing competitive pressures from trade liberalization.

7. POLICY IMPLICATIONS

This study has found that increasing trade openness in more-concentrated industries is associated with growing residual wage gaps between men and women employed in India's manufacturing industries. According to this study's identification strategy, competition from international trade is associated with an increase in wage discrepancies between men and women. These results support the prediction of our theoretical model that under the condition of an increasing discrimination parameter, international trade can lead to wider wage gaps between men and women. In a scenario with declining rents in the more-concentrated sector post-liberalization, firms appear to have favored male workers over female workers in the wage bargaining process. Rather than competition from international trade putting pressure on firms to eliminate costly discrimination against women, pressures to cut costs due to international competition are hurting women's relative pay in the manufacturing sector of India. Lack of enforcement of labor standards that prohibit sex-based discrimination, combined with employer and union practices that favor male workers, leaves women with less bargaining power and limited wage gains compared to men.[18]

If women are bearing a disproportionately large share of the costs of trade liberalization, then a number of policy measures that build women's human capital and strengthen the social safety net may help ease the burden. A policy priority is to achieve gender equality at all education levels so that women have access to the same range of occupational choices as men. Improved educational opportunities also include greater access for working-age women to vocational education; this may be especially useful for women who are displaced as a consequence of increased competition from abroad. Closely related, access to firm-specific training and new programs for accreditation for workers' skills can also help to close the gender gap. By building and up-grading skills, vocational education programs and improved opportunities for on-the-job training can help improve women's ability to obtain a wider range of jobs, which, in turn, can help boost women's relative pay. Additionally, stronger enforcement of India's equal pay and equal opportunity legislation, which dates back to the late 1950s, will reduce discriminatory pay practices that appear to be contributing to rising residual wage gaps in the manufacturing sector.

In this discussion on improving women's relative compensation, it is important to note that attempts to raise the wages of female workers may be counterproductive if firms relocate in order to avoid paying higher wages (Seguino & Grown, 2006). Hence, although wage hikes may be justified in terms of the additional productivity they induce, women employed in highly mobile firms are unlikely to benefit from such legislation. Moreover, employees of such firms may be further adversely affected since mobile firms are also less likely to invest in training. Alternatively, improved enforcement of labor standards and full employment policies can help provide women with more job security, and assist women in gaining access to a wide range of better-paying jobs in occupations that have traditionally been male-dominated. Raising the likelihood that higher wages will stimulate productivity gains and prioritizing gender equality in an open economy may also necessitate measures that slow the speed with which firms can leave a country in response to higher wage legislations (Seguino & Grown, 2006). Capital mobility is also an issue within India. In such a large country with heterogeneous labor markets and business institutions across regions, the response to pressures from trade liberalization can differ across firms within the same manufacturing sectors. Findings in Aghion, Burgess, Redding, and Zilibotti (2005) indicate that local policies and institutional settings played an important role in the reallocation of manufacturing production across regions in India. Careful institutional reforms at the local level will affect whether regions experience manufacturing sector gains or losses as a result of trade reforms at the national level.

To the extent that productivity enhancing policies are not enough to safeguard women who are adversely affected by trade, improved social safety nets can help to ease the burden that many low-wage women face. For example, greater public provision of day-care services for very young children and after-school services for school-age children can help to ease the time and budgetary constraints that face India's factory workers. Furthermore, women employed in export-producing factories often remit high shares of their income back to families in the rural sector, at potentially great personal cost. Poor social safety nets in the rural sector contribute to the reliance on remittances from these women. Policy reforms that create a viable social infrastructure in the rural sector, including social security, will lessen the dependence on remittances and ease the pressure on such workers. By analyzing the effects of the Indian trade liberalization on women's compensation, and by highlighting the fact that female employees of manufacturing industries appear to fare less well as compared to their male counterparts, this study makes an important contribution to the literature and further demonstrates that not everyone benefited equally as a consequence of the reforms.

NOTES

1. Numerous forces at the macro and micro levels can affect the gender wage gap in both directions. For a comprehensive volume on gender and trade, see van Staveren, Elson, Grown, and Çağatay (2007).

2. Agesa and Hamilton (2004) apply a similar methodology to data from the United States in the context of the racial wage gap for men, and they also find little evidence that increasing competition from international trade reduces the racial wage gap.

3. The idea that children bear some of the adjustment costs of trade reforms is consistent with the findings in Menon (2007), which finds that states in India that are unionized have higher incidences of labor unrest, disruptions in household earnings, and child labor.

4. However, in evaluating the role of trade policy reforms, the author concludes that international trade in manufactured goods helped skilled men and hurt skilled women.

5. The consumer optimization problem from which this inverse demand curve is derived is as in Borjas and Ramey (1995).

6. The Cournot model assumes that each firm takes the other firm's quantities produced as given.

7. Theoretically, the value of parameter d may lie between 0 and positive infinity.

8. To prevent distortions from outliers in the mean regressions, individuals with extremely low or high weekly cash wages are dropped from the sample. We trim the bottom and top 0.1 percentiles from the wage distribution.

9. The ASI cover the years 1980–81 to 2004–05, where 1980–81 represents April 1980 to March 1981, and so forth.

10. Although the sample covers only wage employees, it is appropriate to include self-employed as a control variable. According to the NSSO questionnaire, if the household head is self-employed in agriculture or non-agriculture, then the household is classified as being self-employed. However, other members in the household can still be regular/salaried workers.

11. We followed the suggestion in Deaton (1997, pp. 66–72) to calculate both weighted and un-weighted estimators given the lack of agreement on the use of survey weights when household surveys use sophisticated designs in which different households have varying probabilities of been chosen for the sample. Results in Appendix 4 do not differ substantially in terms of magnitude, sign, or precision if we run the wage regressions without sampling weights. To further substantiate this claim, we performed the Dumouchel and Duncan test (an F-test). An insignificant F-test indicates that the weighted and unweighted regressions are not very different. In conducting this test, we found that that F-test is insignificant in three out of the five years of our data [$F(19, 10{,}866) = 1.07$ in 1983, $F(19, 10{,}104) = 0.82$ in 1987–88, and $F(18, 8{,}112) = 1.39$ in 1999–2000, each with $p > 0.10$]. Hence the test indicates that the wage regression is correctly specified for the majority of the years of our data.

12. We observe some variation in the magnitudes of the coefficient estimates in the male wage regressions across years. A detailed set of consistency checks and coding checks leads us to interpret this variation in coefficient magnitudes as an indication of changes in the determinants of wages in the context of substantial fluctuations in economic and social circumstances.

13. These results are available from the authors upon request.

14. In our search for data on four-firm concentration ratios, we came across work in Bhaumik, Gangopadhyay, and Krishnan (2006) on reforms and entry in India's manufacturing sector. The years of the concentration ratios, 1989–90 and 1997–98, corresponded with neither the beginning year nor end year of our study, making it difficult to justify using these data.

15. We also tried using dummy variables for the years. However, because we had to interact each year dummy (excluding the reference year) with trade, with concentration, and with trade and concentration, the number of regressors increased substantially and we were left with too few degrees of freedom given the small sample size. Constrained by sample size, we needed to represent the time element in the model at a more aggregate level, using the time trend and the post-liberalization dummy.

16. Results from all robustness tests discussed in this section are available upon request.

17. Skill and capital intensity are included in the models separately as they are highly correlated (pair-wise correlation coefficient of 0.1911 which is significant at the 95% level).

18. This idea is also supported with evidence in Seguino (1997), which finds that large gender wage gaps in South Korea persisted or grew worse in the face of rapid export growth that depended on female labor.

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APPENDIX 1. DESCRIPTIVE AND REGRESSION ANALYZES: VARIABLES AND DATA SOURCES

Variable	Description	Data source and years covered
Gender wage gap	Male wages − female wages, by industry (residual wages)	National Sample Survey Organization (NSSO): 1983, 1987–88, 1993–94, 1999–2000, 2004
Wage deflator	Wholesale price index for manufactured products	Ministry of Commerce and Industry, Government of India: 1980–81 to 2004–05
Export value	Dollar value of India's exports, by industry	Trade, production and protection database (Nicita & Olarreaga, 2006): 1980–2004
Import value	Dollar value of India's imports, by industry	Trade, production and protection database (Nicita & Olarreaga, 2006): 1980–2004
Tariffs	Average tariff rates, by industry	Trade, production and protection database (Nicita & Olarreaga, 2006): 1990, 1992, 1997, 1999, 2001, 2004; (Gang & Pandey, 1998a, 1998b): 1983, 1989
Domestic output	Total output, in rupees, by industry	Annual Survey of Industries (ASI): 1980–81 to 2004–05
Exchange rate	Average annual rupee/US$ exchange rate	Reserve Bank of India: 1980–81 to 2004–05
Domestic concentration	(1 – No. establishments/output), by industry	Annual Survey of Industries (ASI): 1980–81 to 2004–05

APPENDIX 2. CONCORDANCE BETWEEN ISIC REVISION 2, NIC 1970, NIC 1987, NIC 1998, AND NIC 2004 CODES

Labels	ISIC	NIC 1970	NIC 1987	NIC 1998	NIC 2004
Food products	311–312	200–219	200–219	1511–1549	1511–1549
Beverages	313	220–224	220–224	1551–1554	1551–1554
Tobacco	314	225–229	225–229	1600	1600
Textiles	321	230–263, 266–269	230–264, 267–269	1711–1730	1711–1730
Wearing apparel (except footwear)	322	264–265	265–266	1810	1810
Leather products	323	290, 292–293, 295–299	290, 292–293, 295–299	1820–1912	1820–1912
Footwear (except rubber or plastic)	324	291	291	1920	1920
Wood products (except furniture)	331	270–275, 279	270–275, 279	2010–2029	2010–2029
Furniture (except metal)	332	276–277	276–277	3610	3610
Paper and products	341	280–283	280–283	2101–2109	2101–2109
Printing and publishing	342	284–289	284–289	2211–2230	2211–2230
Industrial chemicals	351	294, 310–311, 316	294, 300–302, 306	2411–2413, 2430	2411–2413, 2430
Other chemicals	352	312–315, 317–319	303–305, 307–309	2421–2429	2421–2429
Petroleum refinery	353	304	314–315	2320	2320
Miscellaneous petroleum and coal products	354	305–307	316–319	2310, 2330	2310, 2330
Rubber products	355	300–302	310–312	2511–2519	2511–2519
Plastic products	356	303	313	2520	2520
Pottery, china, earthenware	361	322–323	322–323	2691	2691
Glass and products	362	321	321	2610	2610
Other non-metallic mineral products	369	320, 324–329	320, 324–329	2692–2699	2692–2699
Iron and steel	371	330–332	330–332	2710	2711–2719
Non-ferrous metals	372	333–339, 344	333–339, 344–345	2720–2732, 2891–2892	2720–2732, 2891–2892
Fabricated metal products	381	340–343, 345–349	340–343, 346–349	2811–2812, 2893–2899	2811–2812, 2893–2899
Machinery (except electrical)	382	350–359	350–359, 388,390–394, 397–399	2813, 2911–2930, 3000	2813, 2911–2930, 3000
Machinery (electric)	383	360–369	360–369, 395–396	3110–3230	3110–3230
Transport equipment	384	370–379	370–379	3410–3599	3410–3599
Professional and scientific equipment	385	380–382	380–382	3311–3330	3311–3330
Other manufactured products	390	383–389	383–387, 389	3691–3699	3691–3699

Source: Created by authors, with reference to Central Statistical Organization (1970, 1987, 1998, 2004), Sivadasan and Slemrod (2006).

APPENDIX 3. SUMMARY STATISTICS FOR REGULAR SALARIED WAGE EARNERS IN MANUFACTURING, 1983–2004

	Male 1983	Female 1983	Male 2004	Female 2004
Variable				
Log real weekly cash wages in rupees	4.055	3.443	4.816	4.138
	(1.015)	(0.900)	(0.936)	(1.113)
Dummy for illiterate individual	0.151	0.455	0.095	0.303
	(0.359)	(0.498)	(0.294)	(0.460)
Dummy for individual with below primary years of schooling	0.135	0.137	0.056	0.035
	(0.342)	(0.344)	(0.230)	(0.184)
Dummy for individual with primary school	0.197	0.114	0.160	0.158
	(0.398)	(0.318)	(0.367)	(0.365)
Dummy for individual with middle school	0.199	0.108	0.272	0.119
	(0.399)	(0.310)	(0.445)	(0.325)
Dummy for individual with secondary school	0.231	0.150	0.251	0.157
	(0.421)	(0.357)	(0.433)	(0.364)
Dummy for individual with graduate school	0.087	0.037	0.166	0.228
	(0.281)	(0.190)	(0.372)	(0.420)
Years of potential experience for individual	20.542	19.605	18.092	19.509
	(11.920)	(12.361)	(11.060)	(12.712)
Years of potential experience for individual squared/100	5.641	5.369	4.496	5.419
	(5.894)	(6.070)	(5.000)	(5.929)
Dummy for individual with no technical education	0.913	0.945	0.874	0.896
	(0.281)	(0.228)	(0.332)	(0.306)
Dummy for individual who is currently married	0.752	0.596	0.698	0.643
	(0.432)	(0.491)	(0.459)	(0.480)
Dummy for scheduled-tribe/scheduled-caste individual	0.154	0.200	0.166	0.156
	(0.361)	(0.400)	(0.372)	(0.364)
Dummy for self-employed individual	0.084	0.168	0.060	0.130
	(0.277)	(0.374)	(0.238)	(0.336)
Dummy for individual of Hindu religion	0.843	0.827	0.856	0.878
	(0.364)	(0.379)	(0.351)	(0.328)
Dummy for households with male heads	0.967	0.770	0.951	0.767
	(0.178)	(0.421)	(0.216)	(0.423)
Dummy for rural areas	0.222	0.395	0.286	0.413
	(0.415)	(0.489)	(0.452)	(0.493)
Number of pre-school children in household	0.599	0.557	0.450	0.280
	(0.844)	(0.847)	(0.728)	(0.616)
Dummy for northern states of India	0.206	0.122	0.261	0.078
	(0.404)	(0.328)	(0.439)	(0.269)
Dummy for southern states of India	0.254	0.507	0.248	0.479
	(0.435)	(0.500)	(0.432)	(0.500)
Dummy for eastern states of India	0.174	0.059	0.070	0.071
	(0.379)	(0.235)	(0.254)	(0.258)
Dummy for western states of India	0.367	0.312	0.420	0.371
	(0.482)	(0.464)	(0.494)	(0.484)
Number of observations	10,909	834	3,540	548

Note: Standard deviations in parentheses. Sample in each year consists of regular salaried workers between 15 and 60 years of age with positive cash wages in the manufacturing industry. Our regressions include interactions of the potential experience variables and the education dummies.

APPENDIX 4. COEFFICIENT ESTIMATES FROM MALE WAGE REGRESSIONS (IN LOG POINTS; STANDARD ERRORS IN PARENTHESES)

	1983	1987–88	1993–94	1999–2000	2004
Dummy for individual with below primary years of schooling	0.397**	0.254	0.482***	–0.244	–0.083
	(0.182)	(0.207)	(0.145)	(0.273)	(0.373)
Dummy for individual with primary school	0.325**	0.209	0.291**	–0.067	0.053
	(0.161)	(0.179)	(0.125)	(0.246)	(0.303)
Dummy for individual with middle school	0.219	0.527***	0.502***	–0.142	–0.214
	(0.154)	(0.179)	(0.119)	(0.228)	(0.280)
Dummy for individual with secondary school	0.675***	0.775***	0.614***	0.127	0.390
	(0.150)	(0.167)	(0.114)	(0.221)	(0.279)
Dummy for individual with graduate school	1.080***	1.353***	1.420***	0.651***	0.791**
	(0.162)	(0.176)	(0.122)	(0.236)	(0.289)
Years of potential experience for individual	0.051***	0.064***	0.053***	0.028*	0.028
	(0.010)	(0.012)	(0.008)	(0.015)	(0.020)
Years of potential experience for individual squared/100	–0.059***	–0.079***	–0.067***	–0.040*	–0.039
	(0.017)	(0.019)	(0.013)	(0.022)	(0.034)
Dummy for individual with no technical education	–0.214***	–0.311***	–0.281***	–0.284***	–0.315***
	(0.035)	(0.033)	(0.021)	(0.038)	(0.047)
Dummy for individual who is currently married	0.114***	0.135***	0.161***	0.122***	–0.001
	(0.028)	(0.032)	(0.021)	(0.029)	(0.045)
Dummy for scheduled-tribe/scheduled-caste individual	–0.074***	–0.039	–0.075***	–0.047**	–0.103***
	(0.026)	(0.030)	(0.019)	(0.023)	(0.038)
Dummy for self-employed individual	–0.175***	–0.189***	–0.152***	–0.032	–0.167***
	(0.034)	(0.037)	(0.024)	(0.028)	(0.059)
Dummy for individual of Hindu religion	–0.003	0.016	–0.001	–0.043	0.038
	(0.025)	(0.027)	(0.018)	(0.031)	(0.040)
Dummy for households with male heads	0.082	0.146***	0.151***	0.198**	0.199***
	(0.052)	(0.053)	(0.033)	(0.095)	(0.064)
Dummy for rural areas	–0.061***	0.193***	–0.028*	–0.002	0.023
	(0.023)	(0.036)	(0.015)	(0.024)	(0.031)
Number of pre-school children in household	0.005	–0.012	–0.006	0.011	0.015
	(0.011)	(0.012)	(0.009)	(0.015)	(0.020)
Dummy for northern states of India	–0.103***	0.022	–0.040**	0.208***	0.169***
	(0.025)	(0.027)	(0.017)	(0.027)	(0.035)
Dummy for southern states of India	–0.248***	–0.206***	–0.213***	–0.005	–0.101***
	(0.024)	(0.025)	(0.016)	(0.027)	(0.035)
Dummy for eastern states of India	–0.186***	–0.033	–0.201***	0.322***	0.052
	(0.027)	(0.030)	(0.019)	(0.042)	(0.056)
Constant	3.172***	2.975***	3.709***	3.838***	4.092***
	(0.150)	(0.167)	(0.116)	(0.236)	(0.281)
Number of observations	10,904	10,142	14,559	8,150	3,540
Adjusted R^2	0.140	0.171	0.259	0.164	0.265

Note: All estimates are from weighted ordinary least-squares regressions.
Our regressions include interactions of the potential experience variables and the education dummies.
* Indicates statistically significant at 0.10 level.
** Indicates statistically significant at 0.05 level.
*** Indicates statistically significant at 0.01 level.