Caste, Female Labor Supply, and the Gender Wage Gap in India: Boserup Revisited

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I. Introduction

The gender gap in wages is a persistent feature of labor markets despite laws mandating equal treatment of women at the workplace. What is just as notable is the variation in the gender wage gap across regions and countries and, in some cases, over time as well. In a cross-country context, observable differences in characteristics and endowments explain only a small portion of the wage gap (Hertz et al. 2009). Since the unexplained component is the dominant one, the geographical variation in the wage gap is commonly attributed to discrimination.

However, discrimination may not be the only reason. If female and male labor are imperfect substitutes, then the wage gap would vary with male and female labor supply. In many regions of the United States, female wages fell relative to male wages during the Second World War (Aldrich 1989; Acemoglu, Autor, and Lyle 2004). By exploiting cross-sectional variation in the change in female workforce participation rates that occurred during World War II, Acemoglu et al. (2004) showed that higher female labor supply increased the gender gap in wages in the United States. In a sample of 22 countries drawn mostly from the Organization for Economic Cooperation and Development, Blau and Kahn (2003) also explored the idea that higher female labor supply can exacerbate the gender wage gap.

In a developing-country context, the role of female labor supply in influencing the gender gap in wages was highlighted in an influential book by Boserup

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(1970). She pointed to the geographical variation in the ratio of female-to-male agricultural wages that existed in India during the 1950s. The gender wage gap was greater in southern states relative to northern states in India, and Boserup ascribed this to the much higher female participation rates in farming in south India.[1] Figure 1 maps the ratio of female-to-male agricultural wages across Indian states for 2004. It is easy to observe a systematic regional pattern—of the same kind as Boserup described 50 years ago. A corresponding north-south divide can also be seen in figure 2, which maps the female days of work in agriculture (per hectare of land) across the Indian states. A prominent exception is Bihar, which has high labor force participation rates and a relatively lower gender wage gap in agriculture.

Boserup's hypothesis is based on raw correlations drawn from wage data across Indian villages in the 1950s. However, the hypothesis is not immediately obvious because variation in female labor supply could affect male wages as well. The extent to which female and male labor are substitutes matters. In addition, there are competing explanations. For instance, there could be gender segregation by task where "female" tasks are possibly paid less than supposedly "male" tasks. Second, the relative efficiency of the ratio of female-to-male labor in agriculture could vary across regions due to differences in agricultural technology, variation in cropping patterns, and agroclimatic conditions. Third, factors that affect the supply of male labor to agriculture, such as nonfarm employment, could also matter to the wage gap. Figure 3 maps the variation in male employment in agriculture (per unit of land). A stark north-south divide is not evident here. Although, a priori, it would seem that variation in male labor supply would not be important in explaining the north-south pattern in the gender wage gap, this needs to be formally tested within an econometric framework. The goal of this article is to explain the spatial variation in the gender gap in agricultural wages in India. In particular, the article asks whether exogenous variations in female as well as male labor supply to agriculture play any part in explaining the gender wage gap.

The effect of male labor supply on the gender wage gap is of independent interest as well. It is well known that the labor flow from agriculture to other sectors has been much more marked for males than for females (Eswaran et al. 2009). So if men have greater access to nonfarm work opportunities, do women working as agricultural labor gain from growth in the nonfarm sector? In trying

[1] "The difference between the wages paid to women and to men for the same agricultural tasks is less in many parts of Northern India than is usual in Southern India and it seems reasonable to explain this as a result of the disinclination of North Indian women to leave the domestic sphere and temporarily accept the low status of an agricultural wage laborer" (Boserup 1970, 61).

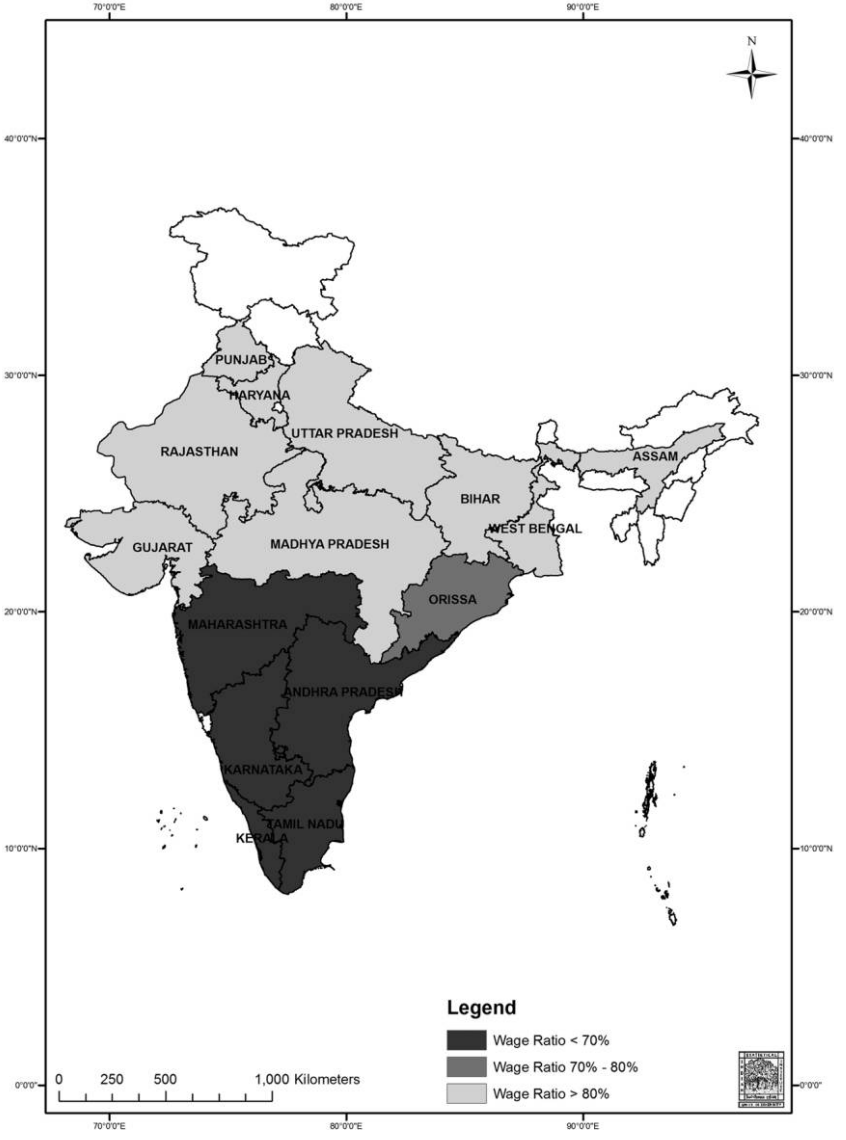

Figure 1. Variation in female-to-male wage ratio across Indian states (rural). Source: National sample survey 2004, schedule 10 (authors' calculations). Indian states not included in the analysis are unshaded.

to understand the impact of economic growth on the economic well-being of women, the effect of nonfarm employment on the gender wage gap is of immense importance. Econometrically, we estimate district-level inverse-demand functions that relate female and male agricultural wages to exogenous variation in female and male labor supply to agriculture. The conceptual challenge is to

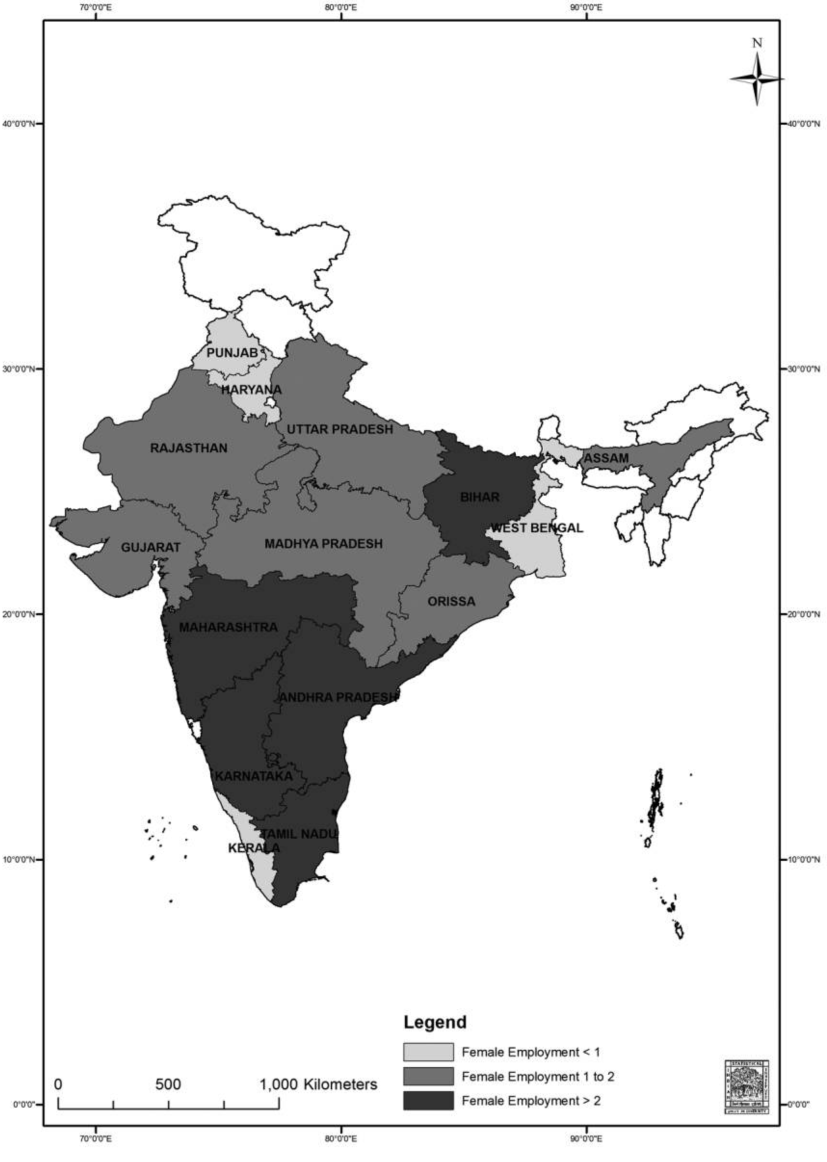

Figure 2. Variation in female employment in agriculture across Indian states (rural). Source: National sample survey 2004, schedule 10 (authors' calculations). Female employment is measured as total days worked in a reference week per unit of land under cultivation. Indian states not included in the analysis are unshaded.

identify exogenous variation in the female and male labor supply to agriculture. The effect of female labor supply on wages is identified by the variation in cultural and societal norms that regulate female labor supply. The pattern of high female workforce participation rates in south India relative to north India has

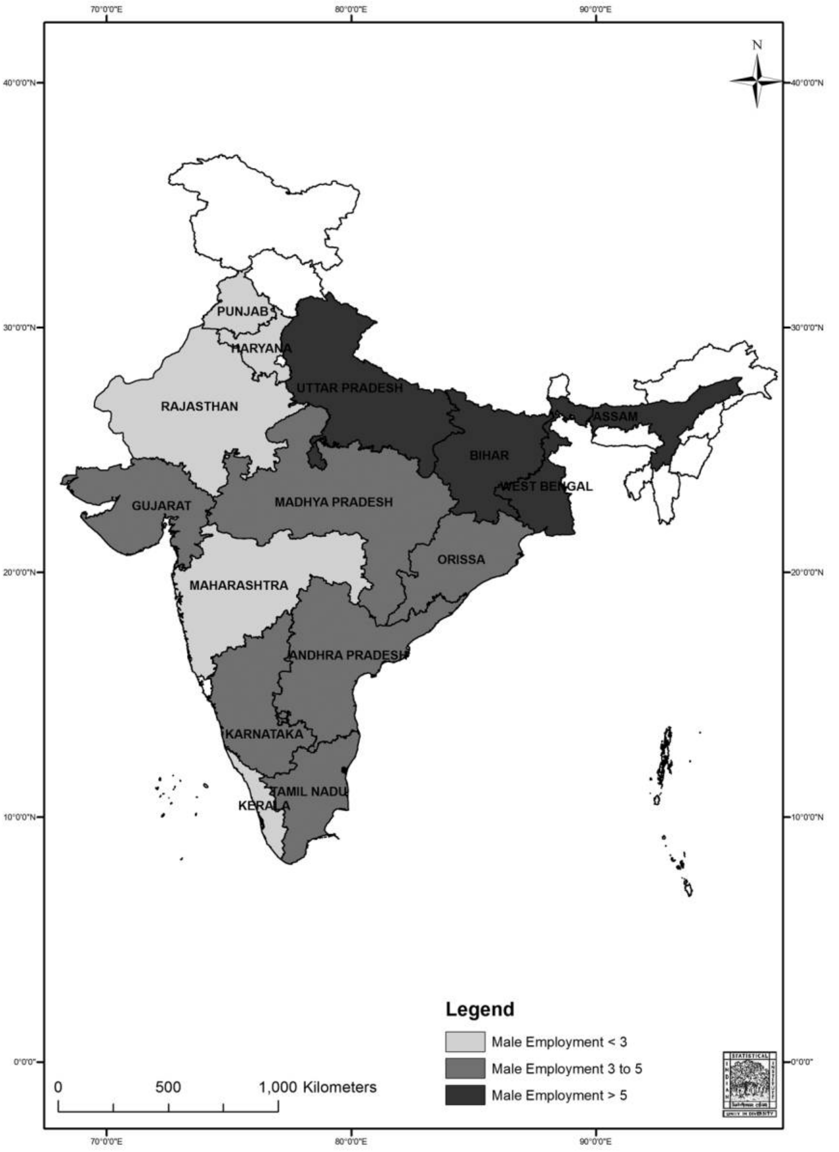

Figure 3. Variation in male employment in agriculture across Indian states (rural). Source: National sample survey 2004, schedule 10 (authors' calculations). Male employment is measured as total days worked in a reference week per unit of land under cultivation. Indian states not included in the analysis are unshaded.

persisted over many decades (K. Bardhan 1984; Nayyar 1987; Chen 1995; Das 2006). Boserup observed that, typically, higher-caste Hindu women take no part in cultivation activities while tribal and low-caste women have traditions of female farming either on their own land or as wage labor. She also points out that tribal and low-caste populations are lower in some states in north India relative to other parts of the country.

The plausibility of social norms driving the north-south divide in female workforce participation is consistent with the well-known finding that women have greater autonomy in the southern states of India (Dyson and Moore 1983). Basu (1992) and Jejeebhoy (2001) find similar patterns in women's status indicators across India's north and south.[2] Boserup's association of social group membership with female workforce participation has been confirmed in later econometric work as well (Chen 1995; Das 2006; Eswaran, Ramaswami, and Wadhwa 2013). Taking a cue from these studies, we take the proportion of households that are low caste as an instrument for female labor supply. The idea that social norms determine women's labor supply decisions is not unique to India (Boserup 1970; Goldin 1995; Mammen and Paxson 2000). What is characteristic of India is the variation of these norms along identifiable social groups.[3]

Figure 4 maps the proportion of the low-caste population across Indian states. Some northern states do have a smaller proportion of the low-caste population (Punjab, Haryana, West Bengal, and Assam), but there are also other northern states (Gujarat, Rajasthan, Uttar Pradesh, Madhya Pradesh, and Bihar) that have low-caste proportions comparable or greater than those in southern states. Therefore, the mechanism hypothesized by Boserup does not bear out in figure 4. Substantively, the instrument of low-caste population might be correlated with variables (such as agroclimatic endowments, infrastructure, and cropping patterns) that also matter to the demand for agricultural labor. These controls must be included for the instrument to be valid.

The proportion of men employed in large-sized nonfarm enterprises instruments male labor supply to agriculture. Large enterprises reflect external demand and are therefore a source of exogenous variation in agricultural labor supply. Figure 5 maps the proportion of men in large industry employment across the Indian states. Again, no distinct geographic pattern can be observed in the distribution of industrial employment. As we argue later, the possible pitfalls in the use of this variable as an instrument are addressed by inclusion of appropriate controls in the estimating equation.

In the next section we relate this article to the relevant literature. In Section III, we provide suggestive evidence in support of Boserup hypothesis. Section IV outlines a theoretical framework that is followed in Section V by

[2] However, Rahman and Rao (2004) do not find such a distinct differentiation across all indicators of women's status.

[3] Cross-country variation in women's participation can also be related to cross-country variation in social norms (Cameron, Dowling, and Worswick 2001).

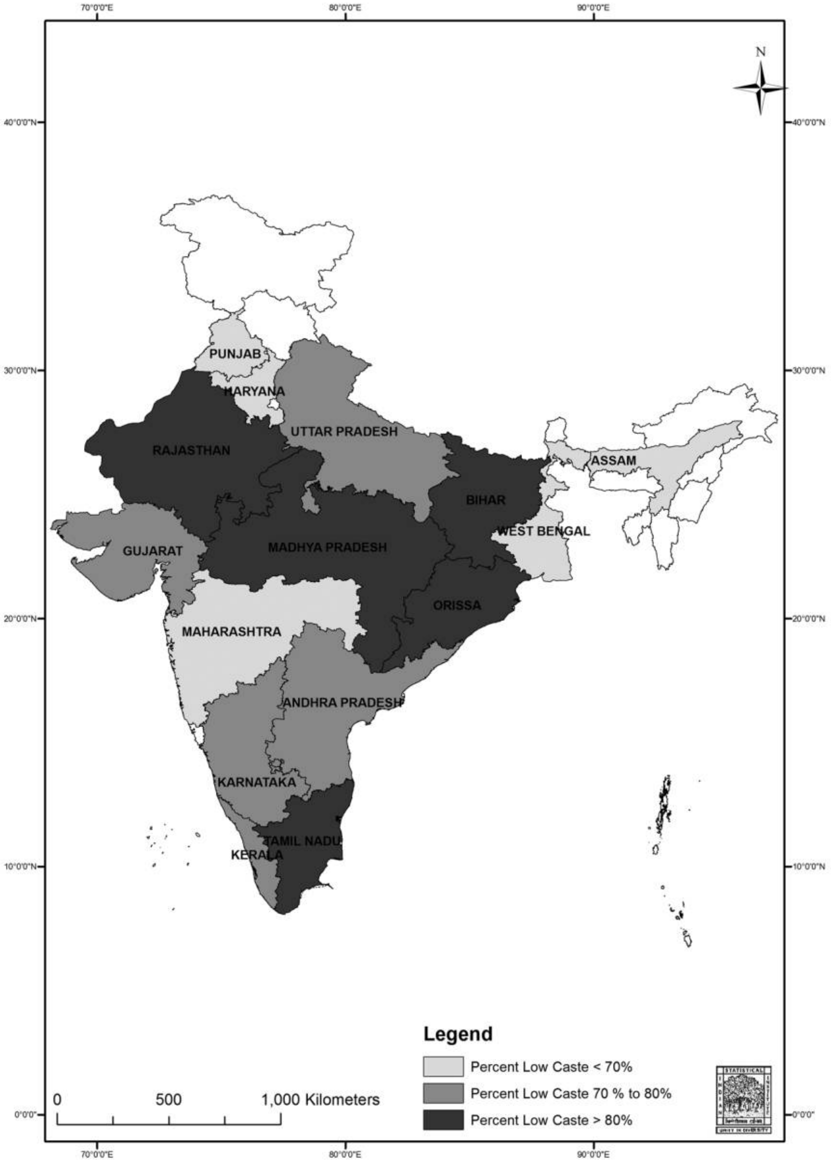

Figure 4. Variation in proportion of low-caste households across Indian states (rural). Source: National sample survey 2004, schedule 10 (authors' calculations). Indian states not included in the analysis are unshaded.

a discussion of the empirical strategy. The data are described in Section VI, and Section VII contains the estimation results. To check for robustness, Section VIII considers alternative specifications. The estimation results are used in Section IX to quantitatively decompose the proportion of wage gap differ-

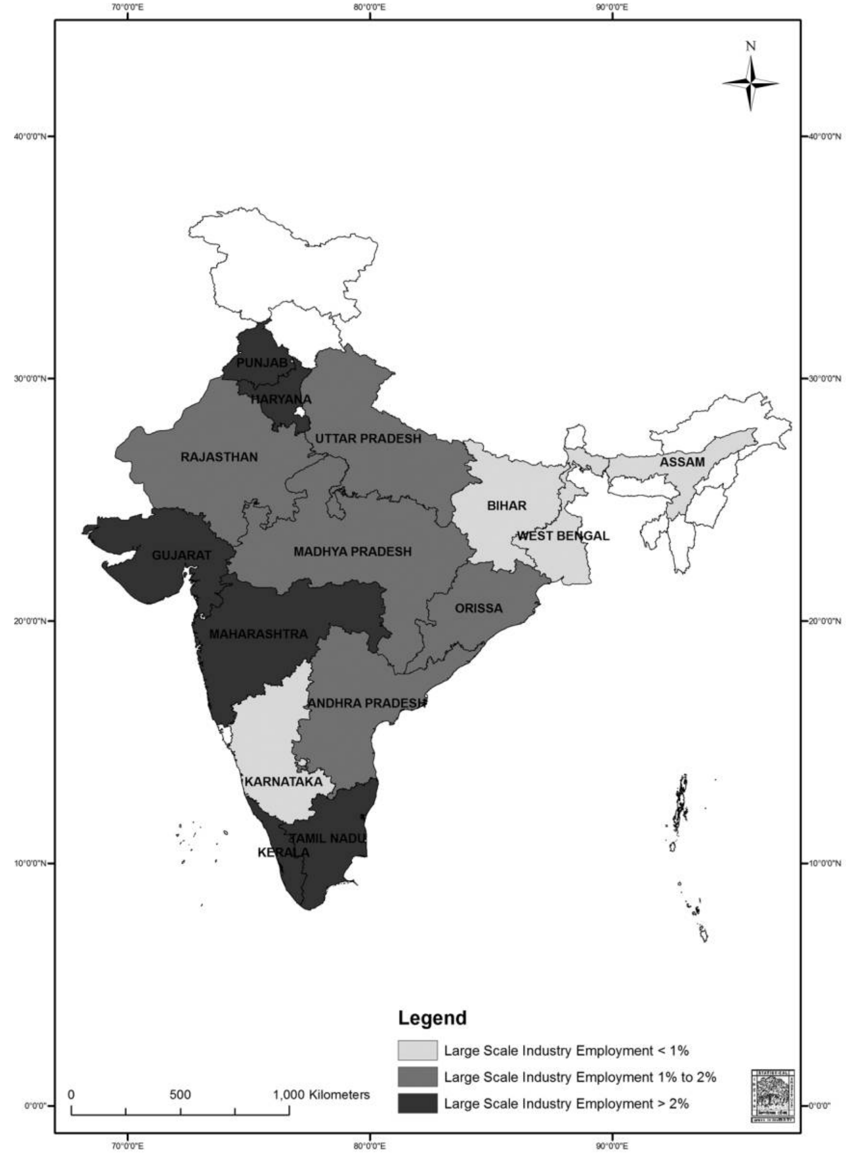

Figure 5. Variation in proportion of men employed in large industry across Indian states (rural). Source: National sample survey 2004, schedule 10 (authors' calculations). Indian states not included in the analysis are unshaded.

ences across northern and southern states of India into its various explanatory components. Concluding remarks are gathered in Section X.

II. Relation to Literature

Blau and Kahn (2003) analyze the gender wage gap across 22 countries and find evidence that the gender gap in wages is lower when women are in shorter supply relative to their demand. They construct a direct measure of female net supply using data across all occupations and recognize that their estimates might be biased because of reverse causality. Acemoglu et al. (2004) correct for the endogeneity of female labor supply using male mobilization rates during World War II as an instrument for the labor supply of females to the nonfarm sector in the United States. They find that an increase in female labor supply lowers female wages relative to male wages. In some specifications, the endogenous variable that is instrumented is the female-to-male labor supply ratio. In other specifications, the female and the male labor supply enter as separate explanatory variables, but only the female labor supply is instrumented.

Rosenzweig (1978) was the first to estimate labor demand functions for agricultural labor in India to estimate the impact of land reforms on male and female wage rates. This exercise is embedded within a general equilibrium market-clearing model of wage determination. In the empirical exercise, Rosenzweig estimates inverse demand and supply equations for hired labor of males, females, and children in agriculture, using wage data on 159 districts in India for the year 1960–61. His results show that an increase in female labor supply has a negative effect on both male and female wage rates. Further, he is unable to reject the null hypothesis that both effects are of equal magnitude.

There are several reasons to revisit this analysis. First, the wage data used by Rosenzweig are not well suited to capturing cross-sectional variation.[4] The better data set for this purpose (which is used in this article) contains the unit-level data from the employment and unemployment schedule of the national sample survey (NSS), which was unavailable to researchers at the time Rosenzweig did his study.[5] Second, as a measure of agricultural labor supply, Rosenzweig uses the percentage of the male (or female) agricultural labor force to the total labor force. However, after controlling for agricultural labor supply, changes in total labor supply should not matter to wages. Our specification for the labor demand function derives from a production function that has land and labor as inputs, and it exhibits constant returns to scale. As a result, the relevant labor supply variable is the agricultural employment (male or female) per unit of cultivated land.

Third, Rosenzweig limits the definition of agricultural labor to hired labor alone. This article, however, estimates the demand for total labor and not for hired agricultural labor. For identification, it is preferable to estimate the in-

[4] Rosenzweig (1978) uses the wage data reported in Agricultural Wages in India (AWI). The problem with AWI is that no standard procedure is followed by states, as the definition of “wage” is ambiguous. Only one village is required to be selected in a district for the purpose of reporting wage data, and the prevailing wage is reported by a village official on the basis of knowledge gathered.

[5] See Rao (1972) and Himanshu (2005) for a discussion about the merits of different sources of data. The consensus is that although the AWI data may work well for long-term trend analysis, they are not suitable for a cross-sectional analysis if the data biases differ across states.

verse demand for all agricultural labor than for hired labor because it is harder to find instruments that are valid for hired labor demand. This is because the instruments that affect labor supply to outside farms would also affect own-farm labor supply and hence potentially affect the demand for hired labor. For instance, higher-caste women may refrain from work outside the home and also limit their work on their own farms. Similarly, availability of nonfarm work opportunities may reduce the family labor supply of landed households to their own farms and increase the demand for hired labor.

Finally, current data allow for more comprehensive controls and better identification strategies than available to Rosenzweig. We employ controls for crop composition, agroecological endowments, and district infrastructure. For identification, Rosenzweig assumes that the demand for hired labor (whether male, female, or child labor) is not affected by the proportion of the population living in urban areas in the district, indicators of the nonfarm economy (factories and workshops per household, percentage of factories and workshops employing five or more workers, percentage of factories and workshops using electricity), and the percentage of the population that is Muslim. We do not use urbanization as an instrument because that could be directly correlated with agricultural productivity by determining the access to technology and inputs. We therefore employ urbanization as a control variable in some of our specifications. We improve on the nonfarm economy instrument by confining it to traded sectors and large enterprises. We replace the percentage Muslim population variable by the proportion of the population that is of low caste.

Other studies that estimate structural demand and supply equations for hired agricultural labor in India are P. Bardhan (1984) and Kanwar (2004). Neither of these studies analyzes male and female laborers separately, and they cover only a few villages in a state. Singh (1996) estimates an inverse-demand function for both males and females in agriculture, using state-level pooled time series data from 1970 to 1989; however, ordinary least squares (OLS) methods are used, and the endogeneity of labor supply is not corrected.

III. The Gender Gap in Wages and Female Labor Supply: Correlations

Figure 6 cross-plots the state-level average of the female-to-male wage ratio against female labor time in agriculture per unit of cultivable land. The figure is based on data from a national survey in 2004 and is consistent with Boserup's hypothesis that the two variables are inversely related.[6]

[6] Kerala, the state with the best human development indicators, is an outlier to the Boserup relation. Like other southern states, its female-to-male wage ratio is low. Unlike other southern states, however, the agricultural female employment (per unit of land) is also low. This is partly because Kerala uses

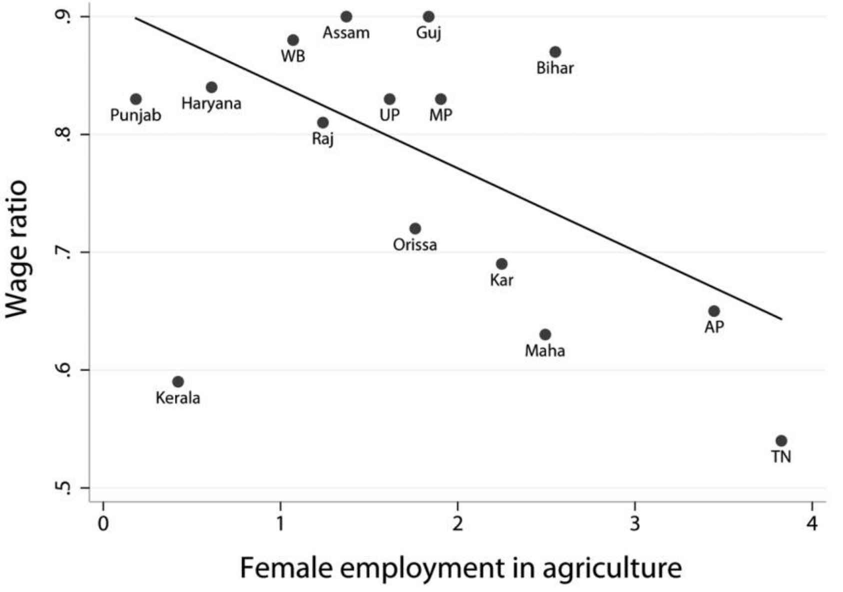

Figure 6. Female employment in agriculture and female-to-male wage ratio. Source: National sample survey 2004, schedule 10 (authors' calculations). Labor employment is measured as total days worked in a reference week per unit of land under cultivation. Population-weighted regression lines are fitted to the plots.

If female and male labor are perfect substitutes in agricultural production, then a change in female labor supply, say a decline, would raise both female and male wages proportionately and not affect the gender wage gap (which in a world without discrimination would be solely due to gender differences in marginal product). For the Boserup hypothesis to hold, female and male labor must not be perfect substitutes so that changes in female labor supply affect female wages more than male wages. The lack of perfect substitutability is closely related to the gender division of labor within agriculture that is often found in many countries (Burton and White 1984; Doss 1999). For instance, in many societies, weeding is usually seen as a task mostly performed by females while plowing is a task done mostly by males. Direct evidence on limited substitutability of female and male labor in agriculture has been found in a number of studies in India and other countries (Laufer 1985; Jacoby 1992; Skoufias 1993; Quisumbing 1996).

If some tasks are better paid than others and if males mostly do the better paid tasks and females do the lower-paying tasks, then that could result in a gender wage gap. In this case, the geographical variation in the gender wage gap could simply be because of variation in the gender division of labor. It is, in fact, true

less labor (female or male) per unit of land than other southern states. So if the female labor supply were measured as a proportion of the male labor supply, Kerala would be substantially closer to the Boserup line, although it would remain an outlier.

that the gender division of labor is more pronounced in the southern states of India.[7] However, this is not the primary reason for either the gender wage gap or its variation.

In table 1, individual wage rates are regressed on gender, age, age squared, education, and marital status. With these control variables, column 1 shows that females get a 35% lower daily wage than males in agriculture. In column 2 we add the controls for the agricultural task for which the daily wage was recorded. The gender wage gap narrows slightly to 33%. Thus, the gender wage gap in Indian agriculture is mostly within tasks.

A direct way of accounting for variation across states in the gender division of labor is to hold it constant and to redo the Boserup plot of figure 6. The female-to-male wage ratio for state s is the weighted mean across tasks given by

$$\frac{w_{fs}}{w_{ms}} = \frac{\sum P_{fjs} w_{fjs}}{\sum P_{mjs} w_{mjs}},$$

where w_{fs} (w_{ms}) is the female (male) wage in state s, P_{fjs} (P_{mjs}) is the proportion of females (males) working in task j in state s, and w_{fjs} (w_{mjs}) is the female (male) wage in task j in state s. Suppose we replace the state proportions in tasks by females and males with the proportions observed for the southern state of Tamil Nadu (arbitrarily chosen), then the wage ratio in state s becomes

$$\frac{w'_{fs}}{w'_{ms}} = \frac{\sum P_{fj,\mathrm{TN}} w_{fjs}}{\sum P_{mj,\mathrm{TN}} w_{mjs}}.$$

Figure 7 plots this measure of the wage ratio, which is devoid of variation in gender division of labor across states, against the female employment in agriculture. The negative relationship between the female-to-male wage ratio and female employment still persists, even when we account for differential participation in tasks by males and females across states in India. As shown earlier, this is because the wage difference across males and females in Indian agriculture is mostly within the same task.

IV. Theoretical Framework

Before proceeding with the empirical strategy, it is useful to discuss the theoretical implications of exogenous changes in male and female labor supply on male and female wages. When the male and female labor supply changes are

[7] This was found by computing, for each state, the proportion of agricultural labor days of males and females spent in each task. An index of gender division of labor (in agricultural tasks) for each state was constructed by considering the Euclidean distance measure between female and male labor proportions.

TABLE 1
GENDER WAGE GAP IN INDIAN AGRICULTURE

	(1)		(2)	
Female	−.35***	(.03)	−.33***	(.03)
Age	.02***	(.00)	.02***	(.00)
Age^2	−.00***	(.00)	−.00***	(.00)
Below primary	.06***	(.02)	.06**	(.02)
Primary	.05*	(.02)	.05*	(.02)
Middle	.03	(.03)	.02	(.03)
Secondary	.04	(.03)	.04	(.03)
Senior secondary and above	−.03	(.03)	−.03	(.03)
Married	−.02	(.02)	−.01	(.02)
Widowed	−.06**	(.03)	−.05	(.03)
Divorced	−.13***	(.04)	−.11**	(.05)
Sowing			−.17**	(.06)
Transplanting			−.04	(.05)
Weeding			−.20***	(.04)
Harvesting			−.12***	(.04)
Other cultivation			−.11***	(.03)
Constant	3.37***	(.05)	3.50***	(.06)
R^2	.21		.22	

Note. OLS regression of individual wage on individual characteristics. Log of wage is the dependent variable. Robust standard errors clustered at state-region level in parentheses. Districts having at least five wage observations for males and females are included. N = 14,190.
* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

exogenous, the resulting impact on wages can be determined by reading off the labor demand curve.

Assume a homogenous, continuous, and differentiable agricultural production function with three factors of production—land (A), male labor (L_m), and female labor (L_f). Returns to each factor are diminishing, and land is fixed in the short run. Let w_m and w_f denote the wage rate for males and females, respectively. Let F_{L_m} and F_{L_f} denote the marginal product of male and female labor, respectively. For given wages, the first-order conditions for labor demand satisfy

$$\ln(w_m) = \ln(F_{L_m}). \tag{1}$$

$$\ln(w_f) = \ln(F_{L_f}). \tag{2}$$

Using the above first-order conditions, we can obtain the own and cross-price elasticities of male and female labor demand.[8] The diminishing return to fac-

[8] The expressions for own and cross-price elasticity of male labor demand are given by $(F_{L_mL_m}/F_{L_m})L_m$ and $(F_{L_mL_f}/F_{L_m})L_f$, respectively. Similarly, expressions for own and cross-price elasticity of female labor demand are given by $(F_{L_fL_f}/F_{L_f})L_f$ and $(F_{L_fL_m}/F_{L_f})L_m$, respectively.

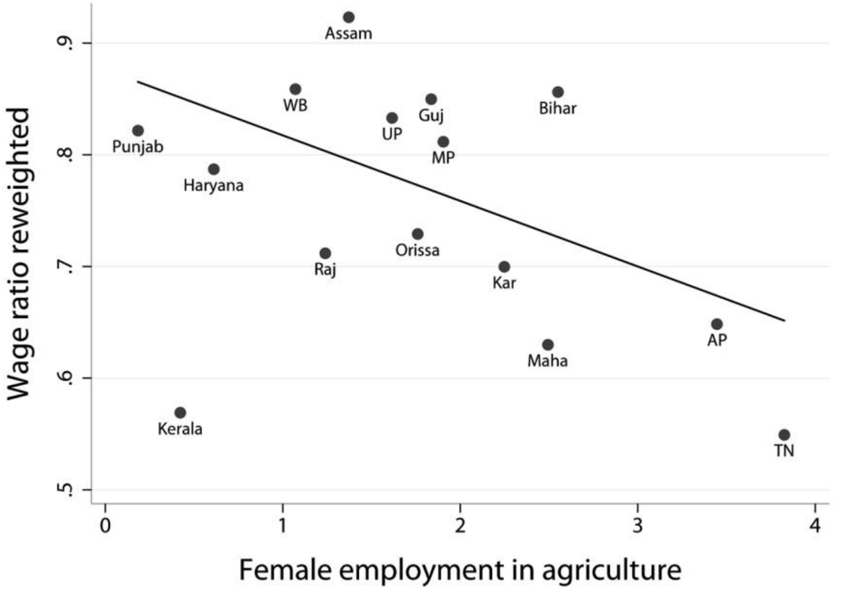

Figure 7. Female employment in agriculture and the reweighted female-to-male wage ratio. Source: National sample survey 2004, schedule 10 (authors' calculations). Labor employment is measured as total days worked in a reference week per unit of land under cultivation. Population-weighted regression lines are fitted to the plots.

tor inputs implies that own-price elasticities are negative. To sign the cross-price elasticity, we need to know whether the male and the female labor inputs are substitutes or complements in the production process. If they are imperfect substitutes (complements) then the cross-price elasticities will be negative (positive).

The effect of female employment on the gender wage gap $(\partial \ln(w_f/w_m)/\partial \ln(L_f))$ cannot be signed if male and female labor are imperfect substitutes. However, the relative magnitude of the cross-price elasticities can be obtained. This is given by

$$\frac{\partial \ln(w_f)}{\partial \ln(L_m)} \Big/ \frac{\partial \ln(w_m)}{\partial \ln(L_f)} = \frac{L_m}{L_f}\frac{w_m}{w_f}. \tag{3}$$

The relative magnitude of cross-price elasticities can, thus, be expressed as a product of the male-to-female labor employment and the male-to-female wage ratio. In the Indian agricultural labor market, labor supply of males is greater than that of females, and male wages are also greater than female wages. Therefore, the effect of male labor employment on female wages will be greater than the effect of female labor employment on male wages. Later, in the article we see whether the estimate of the relative cross-price elasticities, implied by the above theoretical model, holds ground empirically.

V. Empirical Strategy

For observed levels of female and male employment in agriculture, the inverse-demand functions can be written as

$$\begin{aligned} W_{Mi} &= \alpha_0 L_{F,i} + \beta_0 L_{M,i} + \gamma_0 X_i + \varepsilon_{M,i}, \\ W_{Fi} &= \alpha_1 L_{F,i} + \beta_1 L_{M,i} + \gamma_1 X_i + \varepsilon_{F,i}, \end{aligned} \tag{4}$$

where i indexes a district, W is the log of real wages, L is the log of labor employed in agriculture, and X is other control variables. The inverse-demand functions are estimated at the level of a district. This requires Indian districts to approximate separate agricultural labor markets. This has also been assumed in previous studies on Indian rural labor markets (Rosenzweig 1978; Jayachandran 2006) and is supported by the conventional wisdom that inter-district permanent migration rates are low in India (Mitra and Murayama 2009; Munshi and Rosenzweig 2009; Parida and Madheswaran 2010). While some recent work has questioned this, the evidence here points to rural-urban and outcountry migration rather than rural-rural migration (Tumbe 2012). If rural-rural labor mobility across districts is large in India, then the effect of labor supply changes on agricultural wages will be insignificant in a district-level analysis.

From equation (4), it can be seen that the effect of female labor supply on the female-to-male wage ratio is given by $\alpha_1 - \alpha_0$. As α_1 is expected to be negative, an increase in female labor supply leads to a greater gender gap in agricultural wages (i.e., the Boserup hypothesis) if $\alpha_1 - \alpha_0 < 0$. Similarly, the effect of male labor supply on the gender gap in agricultural wages is $\beta_1 - \beta_0$. A decline in male labor supply to agriculture due to greater nonfarm employment opportunities would increase the gender gap in agricultural wages if $\beta_1 - \beta_0 > 0$. Identification requires that we relate wages to exogenous variation in female and male labor supply to agriculture.

Identification of the Impact of Female Labor Supply

For female labor supply, this article uses the proportion of the district population that is low caste as an instrument.[9] The relation between district-level

[9] The definition of "low caste" is as follows. In the employment survey (which is our data source), households are coded as scheduled tribes, scheduled castes, other backward classes and others. Scheduled tribes (ST) and scheduled castes (SC) are those social groups, in India, that have been so historically disadvantaged that they are constitutionally guaranteed affirmative action policies, especially in terms of representation in parliament, public sector jobs, and education. Other backward class (OBC) is also a constitutionally recognized category of castes and communities that are deemed to be in need of affirmative action (but not at the cost of the representation of ST and SC groups). Others are social

female employment in agriculture and the instrument is plotted in figure 8. The positive association between the two is consistent with earlier work that has established the effect of caste on female labor supply. These studies observe that high-caste women refrain from workforce participation because of status considerations (Beteille 1969; Boserup 1970; Bagchi and Raju 1993; Agarwal 1994; Chen 1995). Correlations from village-level and local studies have been confirmed by statistical analysis of large data sets. Using nationally representative employment data, Das (2006) shows that castes ranking higher in the traditional caste hierarchy have consistently lower participation rates for women. The high castes also have higher wealth and income and greater levels of education. So could the observed effect be due to the income effect only? In an empirical model of household labor supply, Eswaran et al. (2013) show that higher-caste households have a lower female labor supply, even when there are controls for male labor supply, female and male education, family wealth, family composition, and village-level fixed effects that control for local labor market conditions (male and female wages) as well as local infrastructure.

The exclusion restriction for identification of the impact of female labor supply on wage rates is that caste composition affects wages only through its affect on the labor supply of women to agriculture. Could the caste composition of a district directly affect the demand for agricultural labor? Das and Dutta (2008) find no evidence of wage discrimination against low castes in the casual rural labor market in India. An earlier village-level study by Rajaraman (1986) also did not find any effect of caste on offered wage in Indian agriculture.

However, the disinclination of higher-caste women to work suggests that their reservation wage ought to be higher. Table 2 shows the results for the regression of individual female wages on a dummy for low caste and other controls. The low-caste dummy is insignificant, controlling for age, education, marital status, type of agricultural operation, and district fixed effects. If the district fixed effects are dropped, then the low-caste dummy is negative and significant even with other district controls. These controls do not, however, capture the across-district variations in male and female labor supply, all of which are included in the district fixed effects. Thus, within a district, differential selection into the labor force does not matter across castes.[10]

groups that are not targets of affirmative action. We define a household to be low caste if it is ST, SC, or OBC.

[10] In another set of regressions, we control for the interaction of caste with the education and the age of an individual. The earnings for low-caste women are lower than those of others for educations levels of graduate and higher.

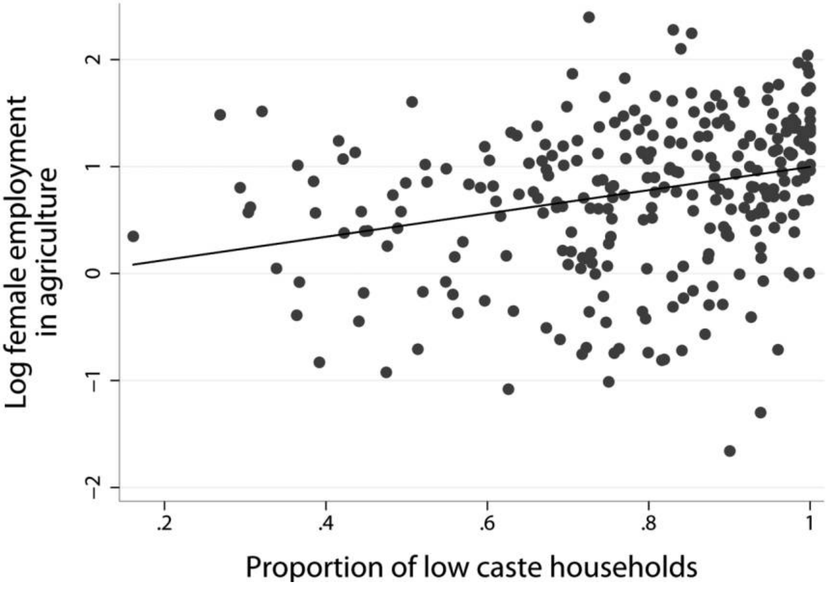

Figure 8. Low-caste households and female employment in agriculture (district). Source: National sample survey 2004, schedule 10 (authors' calculations). Labor employment is measured as total days worked in a reference week per unit of land under cultivation. Population-weighted regression lines are fitted to the plots.

The second concern with caste composition as an instrument is that areas with a greater number of low-caste households may have lower access to inputs, public goods, and infrastructure (Banerjee and Somanathan 2007). Such areas may also have agroecological endowments that are unfavorable to agriculture. For these reasons, we include a comprehensive set of controls for irrigation, education, infrastructure (roads, electrification, banks), urbanization, and agroclimatic endowments.

While there is no ex ante way of knowing whether our controls are good enough, we can perform the following consistency check. Suppose, conditional on our controls, the instrument is still correlated with omitted variables that affect the demand for agricultural labor. Then the caste composition also ought to have an effect on the demand for male labor. This can be easily checked from the first-stage regressions of the instrumental variable procedure. As will be shown later, conditional on controls for agroclimatic endowments and infrastructure, caste composition does not have a statistically significant effect on the employment of male labor in agriculture.

A third possibility is that the caste composition in a district reflects long-run development possibilities. In this story, the higher castes used their dominance to settle in better endowed regions. Once again, this would require adequate controls for agroecological conditions. Finally, could caste composition

TABLE 2
EFFECT OF LOW CASTE ON INDIVIDUAL FEMALE WAGES

	Coefficient	SE
Low caste	−.00	.01
Age	.01**	.00
Age^2	−.00**	.00
Below primary	.01	.02
Primary	.02	.02
Middle	.02	.02
Secondary	.01	.04
Senior secondary and above	.13***	.04
Married	.00	.02
Widowed	−.01	.02
Divorced	−.05	.04
Sowing	−.01	.08
Transplanting	.08	.07
Weeding	−.03	.07
Harvesting	.04	.07
Other cultivation	.02	.06
Constant	3.23***	.08
District fixed effect	Yes	
R^2	.49	

Note. OLS regression of individual female wages on individual characteristics. Log of wage is the dependent variable. Robust standard errors clustered at state-region level shown. Districts having at least five wage observations for females are included. $N = 6{,}377$.
** Significant at the 5% level.
*** Significant at the 1% level.

itself be influenced by wages? Anderson (2011) argues that village-level caste composition in India has remained unchanged for centuries, and location of castes is exogenous to current economic outcomes. This is, of course, entirely consistent with the low levels of mobility in India noted earlier.

Identification of the Impact of Male Labor Supply

For male labor supply, this article uses as an instrument the district proportion of men (age 15–59) employed in nonfarm manufacturing and mining units with a workforce of at least 20, as an instrument. The relation between this instrument and district-level male employment in agriculture is plotted in figure 9. The negative association visible in the graph is consistent with the proposition that competition from nonfarm jobs reduces labor supply to agriculture and increases wages (Lanjouw and Murgai 2009). Rosenzweig's (1978) study of agricultural labor markets also uses indicators of nonfarm economy as an instrument for labor supply to agriculture.[11] However, not all nonfarm activity can

[11] The variables used by Rosenzweig are the number of factories and workshops per household, percentage of factories and workshops employing five or more people, and percentage of factories and workshops using power.

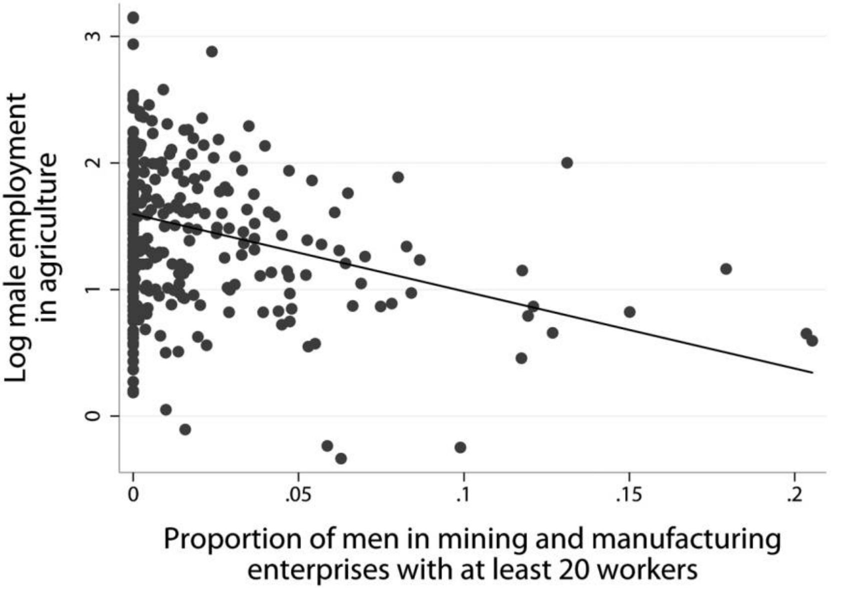

Figure 9. Large-scale industrial employment and male employment in agriculture (district). Source: National sample survey 2004, schedule 10 (authors' calculations). Labor employment is measured as total days worked in a reference week per unit of land under cultivation. Population-weighted regression lines are fitted to the plots.

be considered to be exogenous to agriculture. We define our instrument to include employment in manufacturing and mining sectors and further restrict it to only large-scale units. Our case, elaborated below, is that employment in the nontraded sectors and in small enterprises is endogenous to agricultural development, but that is not so for large enterprises in traded sectors.

The rural nonfarm sector is known to be heterogeneous. Some nonfarm activity is of very low productivity and "may function more as a safety net—acting to absorb labor in those regions where agricultural productivity has been declining—rather than being promoted by growth in the agricultural sector" (Lanjouw and Murgai 2009, 253). These are typically service occupations with self-employment and limited capital. It is clear that such nonfarm activity is endogenous to agricultural wages.

The other case is when prosperous agriculture stimulates demand for nonfarm activity. This type of nonfarm employment tends to be concentrated in the nontraded sector of retail trade and services and mostly in small enterprises. Using a village-level panel data set across India, Foster and Rosenzweig (2003) argue that nontraded sectors are family businesses with few employees, while factories are large employers and frequently employ workers from outside the village in which they are located. In a companion paper, they state that on average nontraded service enterprises consist of two or three workers. This is no different from the international experience of developing countries (World Bank 2007, chap. 9).

Column 1 in table 3 presents the sectoral distribution of nonfarm employment in production units with a workforce of size 20 or more. This can be compared to the sectoral distribution of nonfarm employment in production units with a workforce of size nine or fewer in column 2. It can be seen that manufacturing and mining account for a substantially larger proportion of large work units, while nontradable sectors such as trade and hotels, transport, and construction are less important. These considerations dictate that a valid instrument that captures withdrawal of labor from the farm sector would measure nonfarm employment in large units and in the traded sectors.

Even though the tradable nonfarm goods and services do not depend on local demand, this variable could still be invalid if large nonfarm enterprises locate in areas of low agricultural wages. This possibility is suggested in the work of Foster and Rosenzweig (2004). They analyze a panel data set over 1971–99 collected by the National Council of Applied Economic Research. These data suggest a much higher expansion of rural nonfarm activity than that implied by the nationally representative employment survey data of NSS (Lanjouw and Murgai 2009). To see whether the nonfarm sector gravitates toward agriculturally depressed areas in this data set, Lanjouw and Murgai (2009) estimate the impact of growth in agricultural yields on growth in nonfarm sector employment. They take growth in agricultural yields as a proxy for agricultural productivity and do not find a negative relationship between manufacturing employment and yield growth. They find a positive as-

TABLE 3
SECTORAL DISTRIBUTION OF NONFARM EMPLOYMENT (%)

Industry	Twenty or More Workers (1)	Nine or Fewer Workers (2)
Allied activities in agriculture	1	7
Fishing	0	1
Mining	7	1
Manufacturing	44	20
Construction	11	17
Trade and hotels	3	28
Transport	9	12
Finance and real estate	3	2
Public administration	22	11
Domestic services	0	1

Note. Calculated from the usual activity status of respondents in the national sample survey 2004, schedule 10. Sample includes men age 15–59.

sociation between the two in the specification with state fixed effects and no other district controls. However, the addition of region fixed effects makes the positive relation disappear.

Therefore, if anything, the traded nonfarm sector grew more in areas that were relatively agriculturally advanced. One explanation for this has been provided by Chakravorty and Lall (2005). They analyze the spatial location of industries in India in the late 1990s and find that private investment gravitates toward already industrialized and coastal districts with better infrastructure. No such pattern is seen for government investment. The significance of geographical clusters is that it makes initial conditions of agricultural productivity and infrastructure important in determining future investments. This implies that estimation of labor demand should include adequate controls for infrastructure to sustain the validity of the instrument.

Again, the adequacy of controls that ensure validity of the nonfarm employment instrument may be hard to judge ex ante. However, if the nonfarm employment instrument is correlated with omitted variables that affect overall agricultural labor demand, then the instrument ought to be significant in the first-stage regression for female employment. As we show later, this consistency check shows that nonfarm employment in large manufacturing and mining units is not a significant explanatory variable for female employment in agriculture.

VI. Data

The key data this article uses are from the nationally representative Employment and Unemployment survey of 2004–5 conducted by NSS. The survey contains labor force participation and earnings details for a reference period of a week. Some of the other variables, including the instruments, are also constructed from this data set. The control variables are obtained from a variety of sources (see table A1).

The first set of control variables relates to agriculture: irrigation, inequality in landholdings, rainfall, agroclimatic endowments, and land allocation to various crops. The agroclimatic variables are derived from a classification of the country into 20 agroecological zones (AEZ) described in table 4 (Palmer-Jones and Sen 2003). The independent variables are computed by taking the proportion of the area of a district under a particular AEZ. A second set of control variables relates to infrastructure: roads, electrification, and banking. A third set of variables relates to education and urbanization. Table 5 contains a description of all the variables, their definitions, and descriptive statistics.

The district-level regressions are weighted by the district population, and standard errors are robust and corrected for clustering at the state-region level.

TABLE 4
AGROECOLOGICAL ZONES (AEZ)

AEZ	Description
2	Western Plain, Kachch and part of Kathiarwar, peninsular, hot arid ecoregion, with desert and saline soils and LGP (Length of Growing Period) <90 d
3	Deccan Plateau, hot arid ecoregion, with red and black soils and LGP < 90 d
4	Northern Plain and Central Highlands including Aravelli hills, hot semiarid ecoregion with alluvium derived soils and LGP 90–150 d
5	Central Highlands, Gujarat Plains, Kathiarwar peninsular, hot arid ecoregion, with medium and deep black soils and LGP 90–150 d
6	Deccan Plateau, hot semi arid ecoregion, with mainly shallow and medium but some deep black soils and LGP 90–150 d
7	Deccan Plateau of Telengana and Eastern ghats, hot semiarid ecoregion with red and black soils and LGP 90–150 d
8	Eastern Ghats, Tamil Nadu uplands and Deccan (Karnataka) Plateau, hot semi arid ecoregion with red loamy soils and LGP 90–150 d
9	Northern Plain, hot subhumid (dry) ecoregion with alluvium derived soils and LGP 150–80 d
10	Central Highlands (Malwa, Bundelkhand, an Eastern Satpura), hot subhumid ecoregion, with black and red soils and LGP 150–80 d up to 210 d in some places
11	Eastern Plateau (Chattisgarh), hot subhumid ecoregion, with red and yellow soils and LGP 150–80 d
12	Eastern (Chotanagpur) plateau and Eastern Ghats, hot subhumid ecoregion with red and lateritic soils and LGP 150–80 to 210 d
13	Eastern Gangetic Plain, hot subhumid (moist) ecoregion, with alluvium derived soils and LGP 180–210 d
14	Western Himalayas, warm subhumid(to humid and perhumid ecoregion) with brown forest & podzolic soils, LGP 180–210+d
15	Bengal and Assam Gangetic and Brahmaputra plains, hot subhumid (moist) to humid (and perhumid) ecoregion, with alluvium derived soils and LGP 210+ d
16	Eastern Himalayas, warm perhumid ecoregion with brown and red hill soils and LGP 210+ d
17	Northeastern Hills (Purvachal), warm perhumid ecoregion with red and lateritic soils and LGP 210+ d
18	Eastern coastal plain, hot subhumid to semiarid ecoregion, with coastal alluvium derived soils and LGP 210+ d
19	Western ghats and coastal plain, hot humid region, with red, lateritic and alluvium derived soils and LGP 210+d

Source. Gajbhiye and Mandal (2006).

In some districts, there are very few wage observations. To avoid the influence of outliers, the districts where the number of wage observations for either males or females was fewer than five were dropped from the analysis. Dropping districts where either male or female observations are few in number results in a data set with equal observations for males and females. However, this could lead to a biased sample, as the districts where female participation in the casual labor market is the least are most likely to be excluded from the sample. To see whether such selection matters, we also estimate the male labor demand function for districts in which the number of male wage observations is at least five (ignoring the paucity, if any, in the number of female observations) and similarly estimate the female labor demand function for districts in which

TABLE 5
VARIABLE DESCRIPTION AND SUMMARY STATISTICS

Variable	Definition	Mean	SD
Wage:			
Male wage	ln(real average male casual manual worker wages in cultivation, age 15–59 years)	3.82	.28
Female wage	ln(real average female casual manual worker wages in cultivation, age 15–59 years)	3.54	.31
Labor supply:			
Male LS	ln(total days worked in a reference week in cultivation by males age 15–59/area under cultivation)	1.46	.61
Female LS	ln(total days worked in a reference week in cultivation by females age 15–59/area under cultivation)	.73	.71
Instrument:			
Low caste	Percentage scheduled castes (SC), scheduled tribes (ST), and other backward class (OBC) households	.75	.19
Industry	Percentage men age 15–59 engaged in a manufacturing or mining unit employing more than 20 workers	.02	.03
Agriculture:			
Irrigation	Percentage cultivated area irrigated	.43	.26
Gini	Gini coefficient for landholding inequality	.69	.10
Rainfall	Rainfall received during June–September 2004 in cm	8.30	5.41
Coarse cereals	Percentage area under production of coarse cereals	.16	.19
Cotton	Percentage area under production of cotton, jute, mesta, tobacco, and sugarcane	.08	.11
Oilseeds and pulses	Percentage area under production of oilseeds and pulses	.25	.20
Rice	Percentage area under production of rice	.35	.29
Horticulture	Percentage area under production of horticulture crops	.06	.12
Wheat	Percentage area under production of wheat	.10	.15
Infrastructure:			
Paved roads	Percentage villages accessible by a paved road	.66	.24
Electrified	Percentage villages electrified	.86	.23
Commercial bank	Percentage villages having a commercial bank	.09	.13
Education and urbanization:			
Primary–middle male	Percentage primary–middle educated males age 15–59	.36	.09
Secondary male	Percentage secondary or higher educated males age 15–59	.23	.09
Primary–middle female	Percentage primary–middle educated females age 15–59	.25	.10
Secondary female	Percentage secondary or higher educated females age 15–59	.11	.07
Urban	Percentage population in a district living in urban areas	.27	.18

Note. Weighted means with weights equal to district population.

the number of female wage observations is at least five (ignoring the paucity, if any, of male wage observations).

VII. Main Findings

Table 6 shows the two-stage least squares (2SLS) estimates of inverse-demand functions for total male and female labor in agriculture. The first specification includes only the agriculture controls of irrigation, land inequality, rainfall, agroecological endowments, and allocation of land to various crops. In the second specification, we add the infrastructure controls of roads, electrification, and banking. The final specification includes the controls for education and urbanization. Table 7 shows the coefficients of the instruments in the first-stage

TABLE 6
AGGREGATE DEMAND FOR TOTAL LABOR IN AGRICULTURE

	Male Wage		Female Wage		Male Wage		Female Wage		Male Wage		Female Wage	
	(1)				(2)				(3)			
District control:												
Agriculture	Yes				Yes				Yes			
Infrastructure	No				Yes				Yes			
Education and urbanization	No				No				Yes			
Female LS	−.08	(.17)	−.49*	(.27)	−.11	(.17)	−.54*	(.31)	−.13	(.15)	−.52**	(.25)
Male LS	−.29***	(.09)	−.35***	(.12)	−.23***	(.09)	−.36***	(.14)	−.28***	(.09)	−.37**	(.15)
Irrigation	.21*	(.12)	.30*	(.17)	.28**	(.12)	.41**	(.19)	.31**	(.12)	.41**	(.20)
Gini	−.52	(.37)	−1.28**	(.54)	−.64*	(.34)	−1.33**	(.56)	−.65*	(.33)	−1.30**	(.51)
Rainfall	−.00	(.01)	.01	(.01)	.00	(.00)	.01	(.01)	.00	(.01)	.01	(.01)
Paved roads					.43***	(.10)	.05	(.25)	.47***	(.11)	.08	(.23)
Electrified					−.55***	(.17)	−.41*	(.25)	−.61***	(.18)	−.44*	(.24)
Commercial bank					.04	(.20)	−.01	(.21)	.04	(.17)	−.00	(.21)
Primary–middle female									−.01	(.27)	−.15	(.54)
Secondary female									.39	(.35)	.39	(.66)
Primary–middle male									−.28	(.26)	−.20	(.40)
Secondary male									−.16	(.24)	.04	(.45)
Urban percentage									−.15**	(.08)	−.08	(.16)
Constant	4.50***	(.37)	4.64***	(.49)	4.85***	(.41)	5.08***	(.69)	5.10***	(.49)	5.16***	(.76)
AEZ	Yes				Yes				Yes			
Land allocation to crops	Yes				Yes				Yes			
Underidentified (*p*-value)	.00		.00		.01		.01		.01		.01	
F(excluded instruments) L_F^S	3.93		3.93		3.53		3.53		4.81		4.81	
F(excluded instruments) L_M^S	26.79		26.79		23.90		23.90		17.52		17.52	
Null female labor supply has equal effect on male and female wages (at 5% level)	Reject				Reject				Reject			
Null male labor supply has equal effect on male and female wages (at 5% level)	Accept				Accept				Accept			

Note. Two-stage least squares estimates, instrumenting for labor supply of males and females using low caste and large-enterprise industry employment as defined in table 5. Log of wages and labor supply are used in the regressions. Robust clustered standard errors in parentheses. The unit of analysis is a district, and districts having at least five wage observations for male and female each are included here. $N = 279$.

* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

TABLE 7

FIRST STAGE FOR LABOR SUPPLY BY MALES AND FEMALES TO AGRICULTURE

	Male LS		Female LS		Male LS		Female LS		Male LS		Female LS	
	(1)				(2)				(3)			
Low caste	−.11	(.19)	.70**	(.27)	−.15	(.20)	.66**	(.26)	−.22	(.19)	.79***	(.27)
Industry	−3.86***	(.53)	−.58	(.77)	−3.68***	(.55)	−.29	(.89)	−3.33***	(.59)	−.26	(.97)
R^2	.69		.53		.70		.54		.71		.54	

Note. Corresponding first-stage regressions to table 6. Robust clustered standard errors in parentheses. The unit of analysis is a district, and districts having at least five wage observations for male and female each are included here. $N = 279$.
** Significant at the 5% level.
*** Significant at the 1% level.

reduced-form regressions for each of these three specifications. Table 8 displays the coefficients of the labor supply variables from an OLS regression.

In table 7, for all specifications, we find a significantly positive association between proportion of low-caste households in a district and female employment in agriculture. Similarly, a greater presence of large-scale nonfarm enterprises in manufacturing and mining sectors decreases male employment in agriculture significantly in all the specifications. The F-statistic for the instruments is reported in the bottom of table 6, and it is significant at the 5% level for female labor supply and at the 1% level for male labor supply. The first-stage regressions thus confirm the causal story about these variables: that status norms govern female labor supply and that nonfarm opportunities are primarily received by men.

Note also that the proportion of low-caste households does not affect employment of male labor in agriculture and that the presence of large-scale nonfarm manufacturing and mining enterprises does not affect female labor em-

TABLE 8

ORDINARY LEAST SQUARES AND REDUCED-FORM ESTIMATES OF AGRICULTURAL WAGES

	Male Wage		Female Wage		Male Wage		Female Wage		Male Wage		Female Wage	
	(1)				(2)				(3)			
OLS:[a]												
Female LS	−.07**	(.03)	−.15***	(.04)	−.06**	(.03)	−.15***	(.04)	−.06**	(.03)	−.15***	(.04)
Male LS	−.01	(.05)	.04	(.05)	−.01	(.04)	.05	(.05)	−.01	(.04)	.06	(.05)
R^2	.62		.62		.68		.63		.69		.64	
Reduced form:[b]												
Low caste	−.02	(.11)	−.31**	(.13)	−.04	(.10)	−.30**	(.13)	−.04	(.10)	−.34**	(.13)
Industry	1.15***	(.35)	1.63***	(.42)	.89***	(.33)	1.47***	(.44)	.98***	(.34)	1.37***	(.48)
R^2	.62		.61		.68		.62		.68		.63	

Note. Robust clustered standard errors in parentheses. The unit of analysis is a district, and districts having at least five wage observations for male and female each are included here. $N = 279$.
[a] OLS regression of the dependent variable against total labor employed in agriculture, with other controls the same as in table 6.
[b] Reduced-form regression of the log wage on instruments, with other controls the same as in table 6.
** Significant at the 5% level.
*** Significant at the 1% level.

ployment in agriculture significantly. The significance of this observation is that if, despite the controls, the instruments retained some residual correlation with demand for agricultural labor, then we would expect both instruments to be significant in both the first-stage reduced-form regressions. The fact that this is not so supports the case that these are valid instruments for labor supply to agriculture. Returning to the labor demand equations, the 2SLS estimates of the effect of the female and male labor supply on own wage rates in table 6 are larger in magnitude and statistically more significant than the OLS estimates in table 8 and have the expected negative signs for own effects.[12] The coefficients of the labor supply variables do not change much between the three specifications in table 6. The agriculture controls seem to be the most important in removing the correlation between agricultural labor demand and the instruments.

The cross-effects of labor supply on wage rates are negative in sign. This implies that males and females are substitutes in agriculture. However, male labor and female labor are not perfect substitutes. In the 2SLS regressions with the full set of controls (the third specification), female labor supply has a significant impact on female wages with an inverse-demand elasticity of -0.52. However, the impact of female labor supply on male wages is smaller (around -0.1) and is not significantly different from zero. Thus, a 10% increase in the female labor supply decreases female wages by 5.2%, male wages by 1.3%, and the female-to-male wage ratio by 4%. To test formally that the impact on female wages is greater (in absolute terms) than the impact on male wages, we carry out a chi-square test. In all of the specifications, the chi-square test rejects the null that the coefficients are equal against the alternative that the coefficient of the female labor supply in the female wage regression is higher (in absolute value) than the coefficient of the female labor supply in the male wage regression. This is supportive of the Boserup hypothesis that the caste-driven variation in the female labor supply leads to variation in the gender wage gap in agriculture across regions of India. In particular, greater female workforce participation decreases female wages relative to male wages.[13]

[12] By the Durbin-Wu-Hausman test, the null hypothesis that the employment variables can be treated as exogenous is rejected for all specifications (at the 10% significance level).

[13] Following a reviewer's suggestion, we also estimated the Rosenzweig specification for our data set with instruments that are as close as possible to those employed by him. In these results, the female labor supply has a significantly negative impact on both female and male wages but not on the gender wage gap. This matches the finding of Rosenzweig for the 1961 data. We also find that male labor supply does not have a significant impact on the gender wage gap, even though the impact on male wages is significant and negative and insignificant for female wages. In Rosenzweig's earlier analysis, male labor supply had an insignificant impact on male and female wages and therefore did not matter to the gender wage gap.

In contrast, the effect of male labor supply variation is significant for both male and female wage rates. In the third specification with the full set of controls, the point estimate of the inverse-demand elasticity is -0.37 for female and -0.28 for male wages with respect to male labor supply. Although large-scale nonfarm employment is dominated by men, nonfarm labor demand has favorable effects on female and male wage rates. The point estimates would imply that a 10% decrease in male labor supply increases male wages by 2.8%, female wages by 3.7%, and the female-to-male wage ratio by 1%. A chi-square test, however, does not reject (in all the specifications) the null that the coefficients on male labor supply in the male and female inverse-demand functions are equal. Hence, a decrease in male labor supply to agriculture has no significant impact on the gender wage gap in agriculture.

There is, thus, an asymmetry between the effects of gender-specific variation in labor supply on the wage of the opposite gender. Male labor supply matters to female wages, but the effect of female labor supply on male wages is small and insignificant. Why is this so? The theoretical model posited in Section III predicts that the elasticity of female wages with respect to male labor supply relative to the similar cross-elasticity of male wages is the product of two ratios: the ratio of male-to-female labor employment and the male-to-female wage ratio. The sample estimate of male and female labor employment is 5.17 and 2.57 days per week per hectare of land, respectively, while the sample estimate for male and female wages is Rs 47.3 and Rs 36.13 per day, respectively. This gives an estimate of relative cross-wage elasticities as 2.63. The results in table 6, for the specification with the full set of controls, yield an econometric estimate of the ratio of cross-wage elasticities as 2.84, which is close to the prediction from the theoretical model.

The control variables (i.e., other than the labor supply variables) could also have an effect on the gender wage gap. To ascertain this, a chi-square test was conducted to test for the equality of coefficients for each control variable across male and female demand equations. The null hypothesis of equality of coefficients is rejected at the 5% level of significance for rice cultivation, access to roads, and landholding inequality. Rice-growing areas have a higher demand for female labor, which leads to a higher wage rate for women and translates into a lower gender wage gap. Many researchers have documented greater demand for female labor in rice cultivation due to greater demand for females in tasks like transplanting and weeding (Mbiti 2007), and this result validates their observations. But, access to roads seems to increase demand for only male labor, resulting in a larger wage gap between females and males in districts with better access to roads. Landholding inequality measured by the Gini coefficient for a district significantly negatively affects demand for both males and females, reflecting the well-known feature that large farms use less labor per unit of land than small farms. However, women are more adversely affected than men, resulting in a larger gender wage gap in districts with higher land inequality. Theoretically, the effect of landholding inequality on the gender wage gap is ambiguous (Rosenzweig 1978).

A concern with the 2SLS results is that the first-stage *F*-statistic, although significant, is not very large. Weak instruments could lead to biased estimates and to finite sample distributions that are poorly approximated by the theoretical asymptotic distribution. While such concerns are greater in an overidentified model, the weak-instrument critique suggests caution in interpreting the 2SLS results. As a check for just identified models with possibly weak instruments, Angrist and Pischke (2008) and Chernozhukov and Hansen (2008) recommend looking at the reduced-form estimates (of the dependent variable on all exogenous variables) since they have the advantage of being unbiased. Chernozhukov and Hansen (2008) formally show that the test for instrument irrelevance in this reduced-form regression can be viewed as a weak-instrument-robust test of the hypothesis that the coefficient on the endogenous variable in the structural equation is zero. The sign and the strength of the coefficients in the reduced-form regression can provide evidence of whether a causal relationship exists.

Table 8 shows the results for the coefficients of instruments from the reduced-form regression of male and female wages on instruments and other covariates. The instruments are significant in this regression, and so it can be concluded that the weak-instrument problem does not contaminate the inference from the structural regressions. It can be seen that an increase in the proportion of low-caste households reduces only the female wages. This is entirely consistent with the 2SLS results in which the instrument increases only female labor supply (the first-stage regression), which in turn has a significantly negative impact on female wages only. But, large-scale industrial employment has a significantly positive impact on male and female wage rates. This is also in line with the 2SLS results in which the presence of large enterprises in the nonfarm sector decreases only male labor supply to agriculture, which in turn affects both male and female wages positively.

VIII. Robustness Checks

The third specification in table 6 is our baseline, and we consider the robustness of its estimates. Table 9 adds more agriculture controls: fertilizer per unit of cultivated land and implements (consisting of tractors and power-operated tools) per unit of cultivated land. Including fertilizers (col. 1) does not change the impact of female labor supply on male and female wages, and a 10%

TABLE 9
AGGREGATE DEMAND FOR TOTAL LABOR IN AGRICULTURE WITH ADDITIONAL CONTROLS

	Male Wage (1)		Female Wage (1)		Male Wage (2)		Female Wage (2)		Male Wage (3)		Female Wage (3)	
Female LS	−.10	(.14)	−.46**	(.23)	−.12	(.15)	−.52**	(.26)	−.16	(.16)	−.53*	(.28)
Male LS	−.31***	(.10)	−.44***	(.15)	−.29***	(.09)	−.37**	(.15)	−.28***	(.10)	−.37**	(.16)
Irrigation	.25**	(.11)	.27	(.17)	.31**	(.13)	.40**	(.20)	.33***	(.12)	.39**	(.19)
Gini	−.66**	(.33)	−1.31***	(.48)	−.64*	(.34)	−1.28**	(.51)	−.75***	(.29)	−1.20**	(.47)
Rainfall	.00	(.00)	.01	(.01)	.00	(.01)	.01	(.01)	.00	(.01)	.01	(.01)
Paved roads	.52***	(.11)	.18	(.20)	.49***	(.12)	.09	(.23)	.35***	(.13)	.13	(.26)
Electrified	−.60***	(.18)	−.43*	(.24)	−.62***	(.19)	−.45*	(.24)	−.59***	(.21)	−.50*	(.30)
Commercial bank	−.02	(.19)	−.15	(.19)	.04	(.18)	.00	(.21)	−.04	(.16)	−.01	(.23)
Primary–middle female	−.04	(.26)	−.23	(.52)	−.02	(.27)	−.16	(.54)	.04	(.27)	−.15	(.55)
Secondary female	.07	(.40)	−.35	(.65)	.36	(.33)	.37	(.65)	.38	(.35)	.34	(.66)
Primary–middle male	−.24	(.25)	−.13	(.37)	−.28	(.26)	−.20	(.40)	−.29	(.27)	−.21	(.42)
Secondary male	−.05	(.25)	.30	(.47)	−.14	(.24)	.06	(.45)	−.16	(.25)	.11	(.48)
Urban percentage	−.23***	(.09)	−.27	(.17)	−.15**	(.07)	−.08	(.15)	−.11	(.08)	−.09	(.17)
Fertilizer	.04**	(.02)	.10***	(.03)								
Implements					.08	(.10)	.06	(.12)				
Body mass index (female)									−.00	(.01)	−.01	(.02)
Body mass index (male)									−.01	(.01)	.01	(.02)
Constant	5.13***	(.50)	5.23***	(.75)	5.06***	(.50)	5.13***	(.76)	5.73***	(.60)	4.91***	(.87)
AEZ		Yes				Yes				Yes		
Land allocation to crops		Yes				Yes				Yes		
Underidentified (p-value)	.01		.01		.01		.01		.01		.01	
F(excluded instruments) L_F^S	4.86		4.86		4.60		4.60		3.957		3.957	
F(excluded instruments) L_M^S	15.81		15.81		17.06		17.06		17.25		17.25	

Note. Two-stage least squares estimates, instrumenting for labor supply of males and females using low caste and large-enterprise industry employment as defined in table 5. Log of wages and labor supply are used in the regressions. Robust clustered standard errors in parentheses. The unit of analysis is a district, and districts having at least five wage observations for male and female each are included here. $N = 279$.

* Significant at the 10% level.

** Significant at the 5% level.

*** Significant at the 1% level.

increase in female labor supply increases the gender wage gap by 3.6%. The chi-square test does not reject the equality of male labor supply coefficients across male and female labor demand equations but rejects the equality of female labor supply coefficients. The inclusion of fertilizers does, however, reduce the coefficient of irrigation in both equations to the point that it becomes insignificant in the female labor demand equation. This is possibly because of a high positive correlation (0.4) between irrigation and fertilizer use. Controlling for implements used per unit of land cultivated (col. 2) does not change any of the principal findings of the base specification. Again, the chi-square test does not reject the equality of male labor supply coefficients across male and female demand equations but rejects the equality of female labor supply coefficients.

In a third robustness check, we control for male and female health in rural areas. Nutrition status can affect productivity that in turn could affect rural wages. If nutrition status is correlated with our instrumental variable of low-caste composition, then it could bias our results as well. Adult measures of health in India are not available at the district level. Weight and height measurements are available at the state level from the National Family and Health Survey of 2005–6. The measure of undernutrition is the percentage of rural adults with a body mass index of less than 18.5. Table 9 column 3 shows the structural estimates for the total demand for labor with state-level health controls. The results from the base specification continue to hold. While increase in female labor supply increases the gender wage gap significantly, male labor supply has no impact.

As a fourth check, we reconsider our sample selection rule. Recall that we chose districts for which there were at least five observations for female as well as male wages. While this ensures an equal sample size for males and females, it also entails a risk of dropping districts where female participation in wage work is the lowest. To check robustness, we consider the following alternative. For the male worker sample, we included all districts where there are at least five observations for male wages. Similarly, for the female worker sample, we included all districts where there are at least five observations for female wages. This increases the number of districts from 279 in the matched sample to 359 for males and to 288 for females. Table 10 shows the estimates from the baseline specification on this enlarged sample. The estimates validate our central result that the gender wage gap is sensitive to female labor supply and not to male labor supply. In fact, the effect of female labor supply on the gender wage gap in the enlarged sample is greater. A 10% increase in female labor supply results in a 4.8% decline in the female-to-male wage ratio in the enlarged sample compared to 4% in the matched sample.

TABLE 10
AGGREGATE DEMAND FOR TOTAL LABOR IN AGRICULTURE WITH ALL OBSERVATIONS

	Male Wage		Female Wage	
Female LS	−.05	(.06)	−.53**	(.24)
Male LS	−.36***	(.13)	−.34**	(.16)
Irrigation	.22**	(.10)	.42**	(.19)
Gini	−.46**	(.20)	−1.32**	(.53)
Rainfall	−.01	(.01)	.01	(.01)
Paved roads	.40***	(.12)	.09	(.22)
Electrified	−.60***	(.20)	−.47*	(.24)
Commercial bank	.06	(.22)	−.03	(.22)
Primary–middle female	.08	(.22)	−.24	(.51)
Secondary female	.20	(.30)	.29	(.64)
Primary–middle male	−.21	(.20)	−.16	(.37)
Secondary male	.11	(.26)	.14	(.42)
Urban percentage	−.16*	(.09)	−.01	(.15)
Constant	5.09***	(.50)	5.22***	(.77)
AEZ		Yes		
Land allocation to crops		Yes		
Observations	359		288	
Underidentified (*p*-value)	.02		.02	
F(excluded instruments) L_F^S	8.76		5.54	
F(excluded instruments) L_M^S	6.69		17.03	

Note. Two-stage least squares estimates, instrumenting for labor supply of males and females using low caste and large-enterprise industry employment as defined in table 5. Log of wages and labor supply are used in the regressions. Robust clustered standard errors in parentheses. The unit of analysis is a district, and districts having at least five wage observations for male and female separately are included here for estimating male and female demand equations, respectively.
* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

In a fifth robustness check, we control for differential participation in tasks by males and females across districts. As noted earlier, some agricultural tasks are traditionally deemed as male while others are dominated by women. In Section III, we showed that the gender wage gap in Indian agriculture is within tasks. A very small percentage of the wage gap can be attributed to differential participation of men and women across tasks. To address this issue formally, we regress individual wages on individual characteristics (age, age squared, education dummies, and marital status dummies), district-level female and male labor employment in agriculture (suitably instrumented), other district controls, and dummy variables for agricultural tasks for which the wage is recorded. The agricultural tasks are plowing, sowing, transplanting, weeding, harvesting, and other agricultural activities.

The estimates are reported in table 11. They show that a 10% increase in female labor supply reduces female wages by 5.5% and has no significant effect on male wages. Male labor supply, however, has an identical negative effect on male and female wages.

TABLE 11
IMPACT OF FEMALE AND MALE LABOR SUPPLY ON FEMALE AND MALE WAGES

	Male Wage		Female Wage	
Female LS	−.06	(.23)	−.55**	(.28)
Male LS	−.39***	(.13)	−.40*	(.20)
Observations	7,812		6,378	
Underidentified (*p*-value)	.00		.00	
F(excluded instruments) L_F^S	3.71		5.34	
F(excluded instruments) L_M^S	12.96		13.14	

Note. Two-stage least squares estimates, instrumenting for labor supply of males and females using low caste and large-enterprise industry employment as defined in table 5 and controlling for individual characteristics like age, age^2, education dummies, marital status, and agricultural task along with all district controls in the base specification in table 6. Log of wages and labor supply are used in the regressions. Robust clustered standard errors in parentheses. The districts are restricted to those included in table 6.
* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

Our final robustness check relates to the efficiency of hired labor relative to family labor. All through our analysis, agricultural employment is derived as a simple sum of hired and family labor. This would, however, contradict the accepted notion that family labor is more efficient than hired labor. We show in the appendix that the implication of using an unweighted aggregate is that the estimates could be inconsistent. However, we also demonstrate in the appendix that our findings are robust to reweighting hired labor in terms of efficiency units of family labor.

IX. Explaining the Difference in Wage Gap between Northern and Southern States of India

While our findings support the Boserup hypothesis, there are other factors as well that matter to the gender wage gap. So to what extent does the Boserup hypothesis, that is, the difference in female workforce participation across northern and southern states in India, explain the observed difference in the gender wage gap?

From estimation equation (4), the gender wage gap in a southern state can be written as

$$\begin{aligned}\bar{W}_{M,s} - \bar{W}_{F,s} = {} & (\hat{\alpha}_0 - \hat{\alpha}_1)\bar{L}_{F,s} + (\hat{\beta}_0 - \hat{\beta}_1)\bar{L}_{M,s} \\ & + (\hat{\gamma}_0 - \hat{\gamma}_1)\bar{X}_s + \left(\bar{\varepsilon}_{M,s} - \bar{\varepsilon}_{F,s}\right),\end{aligned} \tag{5}$$

where W is the log of wages, L is the log of the labor supply, X is other district-level covariates included in the empirical analysis, and M and F index males and females, respectively. Similarly, the gender wage gap in a northern state can be written as

$$\bar{W}_{M,n} - \bar{W}_{F,n} = (\hat{\alpha}_0 - \hat{\alpha}_1)\bar{L}_{F,n} + (\hat{\beta}_0 - \hat{\beta}_1)\bar{L}_{M,n} + (\hat{\gamma}_0 - \hat{\gamma}_1)\bar{X}_n + (\bar{\varepsilon}_{M,n} - \bar{\varepsilon}_{F,n}). \tag{6}$$

Subtracting (6) from (5), we obtain

$$\begin{aligned}\left(\bar{W}_{M,s} - \bar{W}_{F,s}\right) - \left(\bar{W}_{M,n} - \bar{W}_{F,n}\right) = {} & (\hat{\alpha}_0 - \hat{\alpha}_1)(\bar{L}_{F,s} - \bar{L}_{F,n}) \\ & + (\hat{\beta}_0 - \hat{\beta}_1)(\bar{L}_{M,s} - \bar{L}_{M,n}) \\ & + (\hat{\gamma}_0 - \hat{\gamma}_1)(\bar{X}_s - \bar{X}_n) \\ & + \left(\bar{\varepsilon}_{M,s} - \bar{\varepsilon}_{F,s}\right) - \left(\bar{\varepsilon}_{M,n} - \bar{\varepsilon}_{F,n}\right).\end{aligned} \tag{7}$$

The ratio $[(\hat{\alpha}_0 - \hat{\alpha}_1)(\bar{L}_{F,s} - \bar{L}_{F,n})]/[(\bar{W}_{M,n} - \bar{W}_{F,s}) - (\bar{W}_{M,n} - \bar{W}_{F,n})]$ is the proportion of the difference in the wage gap across the north and south that is explained by the difference in female labor supply.

To implement this, we let the variables take the average values of northern and southern states respectively.[14] The mean values are listed in table 12. The parameters are drawn from the coefficient estimates of the base specification estimated in column 3 of table 6. Table 13 shows the proportion of the gender wage gap explained by each right-hand-side variable. The proportions for AEZ have not been shown for brevity. One can see that 55% of the regional difference in the gender wage gap is because of the larger female labor supply in the southern states.[15] Greater land inequality and lower area under cultivation of rice in the southern states are other important and significant factors that lead to a greater gender wage gap in the south. Greater electrification, lower male labor supply, and the greater importance of coarse cereal crops

[14] Southern India is defined to include Deccan and regions to the south of Deccan. We classify Andhra Pradesh, Karnataka, Kerala, Maharashtra, and Tamil Nadu as southern states, while Punjab, Haryana, Uttar Pradesh, Assam, Bihar, Gujarat, Rajasthan, Madhya Pradesh, and West Bengal are classified as northern states. Geographically, half of Orissa lies in Deccan and the south region and the other half lies up north. Hence, classifying Orissa in either the north or the south according to the definition is not possible. In the results presented in this section, Orissa is not included in the analysis. As a robustness check, we included Orissa in northern states in one set of analyses and in southern states in a second set of analyses.

[15] When Orissa is included in the north (south), the difference in female labor supply explains 58% (52%) of the difference in wage gap between northern and southern states. The conclusions of the article thus do not change much.

TABLE 12
SUMMARY STATISTICS OF VARIABLES ACROSS NORTHERN AND SOUTHERN STATES

	Northern States		Southern States	
Variable	Mean	SD	Mean	SD
Female LS	.54	.73	.98	.60
Male LS	1.70	.61	1.19	.53
Irrigation	.52	.27	.34	.22
Gini	.66	.10	.71	.09
Rainfall	9.21	4.73	7.12	6.11
Paved roads	.53	.23	.83	.13
Electrified	.75	.27	.99	.02
Commercial bank	.06	.03	.14	.17
Primary–middle female	.23	.10	.27	.11
Secondary female	.09	.05	.15	.07
Primary–middle male	.36	.09	.36	.10
Secondary male	.21	.09	.25	.08
Urban percentage	.23	.18	.32	.18
Coarse cereals	.09	.13	.24	.22
Cotton	.08	.12	.09	.11
Oilseeds and pulses	.22	.20	.30	.19
Rice	.39	.28	.25	.25
Horticulture	.03	.03	.10	.17
Male wage	3.77	.25	3.88	.30
Female wage	3.63	.29	3.43	.29

Note. Weighted means with weights equal to district population. Andhra Pradesh, Karnataka, Kerala, Maharashtra, and Tamil Nadu are classified as southern states while Punjab, Haryana, Uttar Pradesh, Assam, Bihar, Gujarat, Rajasthan, Madhya Pradesh, and West Bengal are classified as northern states.

TABLE 13
EXPLAINED DIFFERENCE IN WAGE GAP BETWEEN NORTHERN AND SOUTHERN STATES (%)

Variable	Wage Gap Explained
Female LS	55
Paved roads	36
Rice	29
Horticulture	10
Gini	10
Rainfall	7
Irrigation	5
Primary–middle female	2
Commercial bank	1
Secondary female	0
Primary–middle male	0
Cotton	−2
Urban percentage	−2
Oilseeds and pulses	−2
Secondary male	−2
Electrified	−13
Male LS	−14
Coarse cereals	−22

(sorghum and millets) should lead to a lower wage gap in the south, but these do not affect the gender wage gap significantly in the regressions.

X. Conclusion

The effect of variation in female work force participation on the gender wage gap in developed countries has been explored in recent papers. In a developing-country context, such a connection was made by Boserup (1970) many decades ago. On the basis of data from the 1950s, she posited that the gender wage gap was higher in the southern states of India relative to the northern states because of the greater female labor supply in south India, which stemmed from differences in cultural restrictions on women's participation in economic activity. This article confirms the hypothesis within a neoclassical framework of labor markets. Compared to the literature, this article also pays attention to the variation in male labor supply and how that affects the gender wage gap. The exogenous variation in labor supply was identified by spatial variation in caste composition and nonfarm employment of men in large units.

We find that female labor supply has a sizable effect on female wages but not so much on male wages. This result thus has important implications for the literature on gender wage differentials. It shows that the usual approach of attributing the gender wage gap to only individual characteristics or discrimination is incomplete. The overall labor market structure that determines labor supply and the substitutability between female and male labor may also have a significant impact on gender wage inequality.

The article also found that male labor supply has sizable effects on male as well as female wages. This finding is interesting on three counts. First, it provides a causal effect of withdrawal of males from agriculture due to nonfarm employment opportunities on wages of men and women. The article, therefore, sheds light on the economic processes that affect agricultural wages (Foster and Rosenzweig 2003; Eswaran et al. 2009; Lanjouw and Murgai 2009). Second, the strong effect of male labor supply on female wages is of independent interest since the sectoral mobility of women from the farm to the nonfarm sector is much less marked compared to men (Eswaran et al. 2009). This could be because of lower education levels as well as societal constraints that limit female participation in most nonfarm jobs. This raises a concern that rapid growth in the nonfarm sector does not entail much gain for women. Our finding, however, suggests that there is enough substitutability between men and women in the agricultural production process that a withdrawal of men from agriculture has positive effects on male and female wages.

Finally, the findings point to a marked asymmetry between the effects of female and male labor supplies. Female labor supply does not affect male wages significantly, but male labor supply does move female wages significantly. A standard neoclassical model predicts this asymmetry, and its magnitude is determined by the gender gap in wage and the gender gap in labor supply. The findings match the prediction closely.

Appendix

TABLE A1
DATA SOURCES

	Source
Wages, labor supply, Gini, education, low caste, industry	National sample survey 2004–5
Irrigation, land under cultivation	Land use statistics 2004–5
Fertilizer	Fertilizer Association of India 2004–5
Crop composition	Area, production, and yield statistics 2004–5
Rainfall	India Water Portal 2004–5 (data originally collected by Indian Meteorological Department)
Agroecological zones	Compiled by Richard Palmer-Jones and Kunal Sen
Urban, paved roads, electrified, and commercial banks	Census of India 2001, village directory
Implements	Livestock census 2003

Family versus Hired Labor

We consider the possibility that hired and family labor may not be equally efficient. Family labor may be more efficient because of better incentives. If this is so, a simple aggregate of family and hired labor is not valid and could lead to inconsistent estimates. Suppose one unit of hired labor is equivalent to θ units of family labor (with θ less than one). Then in terms of efficiency units of family labor, the total labor supply is $L_s^f + \theta L_s^o$, where L_s^f and L_s^o are the aggregate labor supply to home farm and to outside farms. In the regressions, we have measured labor supply as $\ln(L_s^f + L_s^o)$. Since $\ln(L_s^f + \theta L_s^o) = \ln(L_s^f + L_s^o) + \ln[(L_s^f + \theta L_s^o)/(L_s^f + L_s^o)]$, the second term is absorbed in the error term of the regressions. This could lead to inconsistent estimates. The instruments will be correlated with $\ln[(L_{Fs}^f + \theta L_{Fs}^o)/(L_{Fs}^f + L_{Fs}^o)]$ if they affect not only the total labor supply but also the allocation of labor between own farm and outside farm. It is possible that low-caste women have a greater propensity to work outside their family farm because of fewer social restrictions. Similarly, the opportunity of employment in manufacturing and mining could lead landed households to divert their labor supply to industry and increase hiring of labor on their farms.

To meet these concerns, we estimate the baseline specification for values of $\theta = \{0.5, 0.7, 0.9\}$, for both male and female labor. The results are shown in table A2. The last column shows the results with $\theta = 1$, which corresponds to the results of the base specification in table 6. As the value of θ decreases, the impact of female labor supply on male wages does not change, but the impact of female labor supply on female wages falls in magnitude. The chi-square test for the equality of the impact of female labor supply on female and male wages continues to be rejected for the selected values of θ. A decrease in the value of θ increases the impact of male labor supply on both male and female wages. Once again, the chi-square test for the equality of the impact of male labor supply on male and female wages is not rejected for the selected values of θ.

TABLE A2

AGGREGATE DEMAND FOR TOTAL LABOR IN AGRICULTURE WHEN TOTAL LABOR IS MEASURED IN EFFICIENCY UNITS

	$\theta = .5$		$\theta = .7$		$\theta = .9$		$\theta = 1$	
Male wage:								
Female LS	−.12	(.15)	−.13	(.15)	−.13	(.15)	−.13	(.15)
Male LS	−.37***	(.13)	−.32***	(.11)	−.29***	(.10)	−.28***	(.09)
Female wage:								
Female LS	−.47*	(.26)	−.50**	(.25)	−.52**	(.25)	−.52**	(.25)
Male LS	−.58***	(.22)	−.47***	(.18)	−.40**	(.16)	−.37**	(.15)

Note. Two-stage least squares estimates, instrumenting for labor supply of males and females using caste and large-enterprise industry employment as defined in table 5. Log of wages and labor supply are used in the regressions. Robust clustered standard errors in parentheses. The unit of analysis is a district, and districts having at least five wage observations for male and female each are included here.
* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

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