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What Explains the Stagnation of Female Labor Force Participation in Urban India?

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Abstract

Female labor force participation rates in urban India between 1987 and 2011 are surprisingly low and have stagnated since the late 1980s. Despite rising growth, fertility decline, and rising wages and education levels, married women's labor force participation hovered around 18 percent. Analysis of five large cross-sectional micro surveys shows that a combination of supply and demand effects have contributed to this stagnation. The main supply side factors are rising household incomes and husband's education as well as the falling selectivity of highly educated women. On the demand side, the sectors that draw in female workers have expanded least, so that changes in the sectoral structure of employment alone would have actually led to declining participation rates.

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India's economy has grown rapidly over the past two decades, with the services sector accounting for a large share of growth (Bosworth and Collins 2008). India has also experienced a sizable fertility decline, a rapid education expansion, and a decline in the education gender gap, while the labor market returns to education increased (Kijima 2006; Pieters 2010). Against this background, it is puzzling to see that the reported female labor force participation rate in urban India has stagnated at around 18 percent since the 1980s. Considering these circumstances, one would expect a rising share of women to enter the labor force, especially in urban India where women have gotten much more educated and where white-collar jobs are concentrated.

The aim of this paper is to investigate why female labor force participation (FLFP) in urban India stagnated despite rising education levels and rapid economic growth. Standard labor supply models and previous research on FLFP and economic development (Goldin 1994; Mammen and Paxson 2000; Blau and Kahn 2007) suggest that rising education and growth of white-collar services employment should draw more women into the labor force by increasing their earnings capacity and reducing social stigma against women's work. On the other hand, rising household incomes could lead to a withdrawal of women from the labor market due to well-known income effect. India is not the only country where female labor force participation has stagnated despite overall growth, fertility decline, and rising female education. In the Middle East and North Africa, one can observe vast and persistent gender gaps in employment despite rising female education levels in many countries. This has been partly ascribed to conservative social attitudes towards women's work in the region (see Gaddis and Klasen 2014), and similar factors might be at play in India as well.

Understanding the causes of stagnation in FLFP matters for several reasons. India currently has an advantageous age structure of the population with a large and growing share of working age people and relatively few dependents. Optimistic predictions for India's future growth often refer to this demographic dividend, which is alleged to have accounted for about a third of East Asia's high per capita growth rates in the period between 1965 and 1990 (Bloom and Williamson 1998; Bloom 2011). However, the benefits of a country's demographic dividend hinge on the productive employment of the male and female working-age population,. In fact, high and rising female employment levels contribute to greater productivity growth (World Bank 2011) and have in fact been critical in sustaining East Asia's high economic growth rates (Klasen and Lamanna 2009; Young 1995).

Beyond women's contribution to growth, stagnation in FLFP has implications for the degree to which women benefit from growth. Employment and earnings are robust determinants of bargaining power, with impacts on female and children's well-being (Qian 2008; Anderson and Eswaran 2009; Afridi et al. 2012). If there are structural economic or cultural barriers preventing women's labor force participation, women are unable to capitalize on these opportunities.

In this paper, we estimate a simple model of female labor force participation using individual level cross-section data spanning the period 1987 to 2011. The model is estimated separately for each survey year and for women with low and high educational attainment. Our estimation results provide a detailed account of the impact of various factors on women's labor force participation and their changes over time. We find a strong conditional relationship between education and labor force participation that is U-shaped, which points at the importance of social stigma for women to work in low-skilled jobs. Accordingly, we show that women with low education appear to be boxed in by the necessity to work if household incomes are very low or insecure, and stigmas attached to working in low-skilled jobs if they are somewhat more educated and in more secure economic environments. Highly educated women appear generally less constrained by family circumstances in their labor force participation decision.

The estimates are further used to decompose the stagnation of FLFP between 1987 and 2011 into contributions by different covariates and changes in behavior and unobservables (Fairlie 2006). On the supply side, we find that rising male incomes and education contributed to a withdrawal of women from the labor force, showing that the classic income effect is at work in urban India. On the demand side, changes in the sectoral structure of employment account for a further reduction in FLFP, in particular related to the declining shares of agriculture and manufacturing which tend to employ more women (particularly in recent years).

The effect of rising female education on female labor force participation is more complicated. Besides a U-shaped relationship between education and labor force participation, our estimates show a large decline in the positive participation effect associated with secondary and graduate education. As a result, the substantial increase in educational attainment of women contributed only moderately to FLFP growth. We provide suggestive evidence that the declining positive effect of higher education is partly accounted for by an erosion of positive selection into higher education, that is, a declining correlation between determinants of higher educational attainment and unobserved determinants of labor force participation. Reasons for this could be the rapid expansion of education supply, but also rising marriage market returns to education, leading women to pursue higher education regardless of their expected labor market attachment.

The paper is organized as follows. Section I discusses the literature on female labor force participation determinants, focusing in particular on economic development and rising education levels. Section II describes patterns of FLFP, wages, education, and employment in urban India. Section III presents our empirical FLFP model and estimation results, followed by the decomposition analysis in Section IV. Section V further investigates the relationship between women's education and labor force participation. Section VI concludes.

I. Development, Education, and Female Labor Force Participation

Labor force participation decisions can be the outcome of individual preferences of the woman, her family circumstances, as well as labor demand conditions for jobs that women are particularly suited for, or where employment in these jobs is seen as socially acceptable. Education can play a key role in shaping these supply and demand conditions. We will discuss these issues in turn.

A common starting point for the analysis of female labor force participation is the basic static labor supply model (see Blundell and MaCurdy 1999), in which an increase in the wage rate reduces demand for leisure as its opportunity cost rises, increasing labor supply. If leisure is a normal good, an increase in a person's income will increase the demand for leisure and thus reduce labor supply. These are the well-known substitution and income effects. For a person currently not working, an increase in the wage rate only has a substitution effect, increasing her incentive to work (i.e., one would always expect a positive own wage effect at the extensive margin). An increase in unearned income (nonlabor income or labor income earned by other household members, particularly the husband) constitutes a pure income effect and therefore reduces labor force participation.

In initial stages of economic development, education levels typically increase much more for men than for women. Women's wages and opportunities for work change relatively slowly while their husband's income rises fast, so the negative income effect is likely to dominate any positive substitution effect of rising female wages. This is what drives reductions in FLFP according to the so-called Feminization-U hypothesis (Boserup 1970; Goldin 1994; Mammen and Paxson 2000; Gaddis and Klasen 2014).[2] Participation is further reduced because of social stigma against women working outside of the home, especially in factory work, and the difficulty of combining household

[2] Though the feminization-U is sometimes considered a stylized fact, the empirical evidence in support of it is mostly based on cross-country analysis, while panel analyses have produced mixed results (Tam 2011; Gaddis and Klasen 2014).

production with market work in nonagricultural occupations; these effects are held to be particularly strong for married women.

In later stages of development, women's education starts to catch up to men's, their earnings capacity increases and they gain access to socially acceptable types of work, especially if demand for white-collar workers increases with the expansion of the services sector. This will result in higher FLFP,[3] but country-specific labor demand conditions clearly play a role in this process. The increase in FLFP could depend on growth in employment opportunities of the kind deemed appropriate for educated women, relative to growth in the educated working age population. Boserup (1970) describes how the feminization of clerical jobs proceeds very slowly when the number of educated men is in excess of demand for clerical workers. In those cases, there is likely to be considerable resistance against women's employment in white-collar jobs, as this would reduce the opportunities for men (Boserup 1970: chapter 7). How the education-labor force participation link evolves over time will thus depend on the structure of labor demand growth in the economy and the status associated with different types of work.[4] If female labor mobility is limited, as is the case in India, the growth in desirable jobs relative to the educated population can generate local mismatches with impacts on female labor force participation rates.

One might further hypothesize that similar factors produce a U-shaped relationship between economic or educational status and women's labor force participation at a given point in time within a country—as is indeed observed in India. Among the poorest with no or very little education, women are forced to work to survive, while among the very highly educated, high wages

[3] Over the course of development, changes in circumstances may also be accompanied by changes in women's behavior, i.e., the degree to which wages, income, and social restrictions affect FLFP. As Goldin (1990) describes the history of women's work in the United States, economic development is reflected in an increasing own wage effect while women's responsiveness to other family income declines. Blau and Kahn (2007) and Heim (2007) find similar evidence for women in the United States.

[4] A gender assessment for Pakistan (World Bank 2005) shows that the increase in urban female labor force participation in the 1990s was driven by an increased demand for teachers. But overall, still a much higher proportion of urban men than women are engaged in white-collar jobs.

induce women to work and stigmas militating against female employment in white-collar jobs that are open to highly educated women are low. Between these two groups, women face barriers to labor force participation related to both the absence of an urgent need to work (the income effect), and the presence of social stigmas associated with female employment in menial jobs.

A correlation between education levels and labor force participation can also appear when both are outcomes of unobserved preferences for work (e.g., related to family background), such that women with a greater taste for work are more likely to attain higher education. Recent research has shown that primary and secondary school enrollment in India respond to the perceived returns to schooling, in particular, the availability and awareness of job opportunities in business and IT-services (Jensen 2012; Shastry 2012; Oster and Millett Steinberg 2013). These studies also show, however, that responses are limited to very local opportunities and that girls' schooling is affected by active recruitment rather than the mere availability of jobs (Jensen 2012). It apparently takes more than growth and rising wages to raise awareness of labor market opportunities, and despite its fast growth, the business services sector still accounts for only a small share of total employment in India. Nonetheless, when analyzing the effect of education on labor force participation it is important to keep in mind the potential endogeneity of education through nonrandom selection into education.

Education could be endogenous to labor force participation in the exact opposite direction as well. In India, social restrictions on the lifestyles of women tend to become more rigid as households move up in the caste hierarchy (Chen and Drèze 1992). If education of women and restrictions on women's mobility and work both increase with families' social status, one would observe a negative correlation between education and labor force participation, at least for some levels of education. Eswaran et al. (2013) find supporting evidence for this negative endogeneity channel in rural India (based on data for 1998–99), but Das and Desai (2003) find no support in a sample of rural and urban women in India in 1993–94.

In all, major determinants of women's labor force participation over the course of economic development are income, wages, and access to jobs deemed appropriate for women. Education levels shape female labor force participation partly through these channels. But women's education is likely to reflect other, unobserved determinants as well. We analyze the role of education and other determinants in detail in our econometric analysis in Section III. First, Section II gives a descriptive analysis of the most important trends in the data.

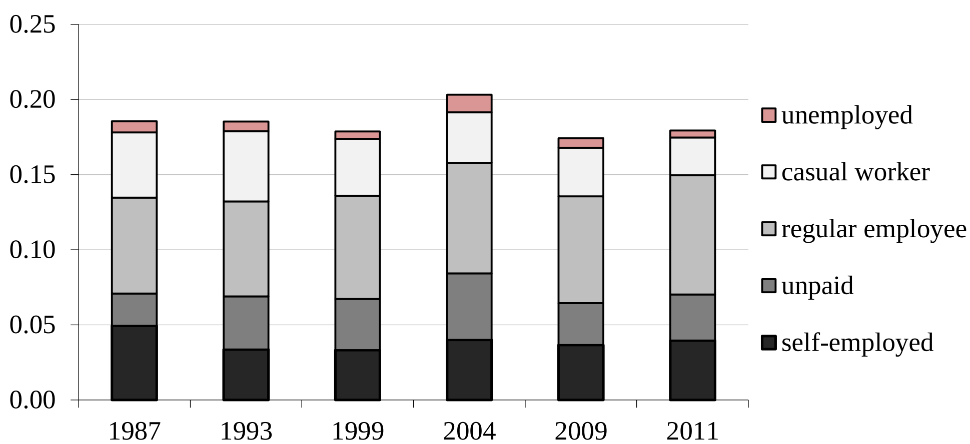
II. Female Labor Force Participation in Urban India

The descriptions and empirical analysis in this paper are based on the so-called thick waves of the NSS Employment and Unemployment Survey, in 1987–88, 1993–94, 1999–2000, 2004-–05, 2009–10, and 2011–12 (henceforth 1987, 1993, 1999, 2004, 2009, and 2011). This cross-sectional survey is the official source of nationally representative employment and earnings data used by the Government of India.

Before discussing labor market developments in urban India in detail, Table A1.1 in appendix 1 summarizes the trends in the female population and labor force for urban and rural India, for different age groups. Female population growth in the age group 15–64, and especially 25–54, exceeds total female population growth. Due to this demographic change, the female labor force has almost doubled in urban India and stayed constant in rural India, despite stagnating female labor force participation rates in urban India, and declining rates in rural India. In that sense, India is already benefitting from its demographic dividend related to a favorable age structure (although to a much lower extent than it would if more women were working). As still more than two-thirds of the Indian population lives in rural areas, the rural trend of declining participation rates dwarfs the urban trend, so that overall female labor force participation declined from 22 percent in 1987 to 17 percent in 2011. Note, however, that rural numbers are more likely to suffer from underreporting of women's work in agricultural activities.

In our analysis we focus on married women in urban India in the age group 25–54. Their labor force participation rate fell slightly from 18.5 percent in 1987 to 17.9 percent in 2011. Breaking down the labor force into different components, one can see in Figure 1 there has been little change in the different types of work and unemployment rates of married women, except for a peak in self-employment and unpaid family work in 2004.[5] Throughout the period, the labor force participation rate of urban married men in the same age group was stable at around 97 percent and hardly differs by education levels.

Figure 1: Urban female labor force participation rate



Note: Married women age 25-54. Self-employment includes employers and own account workers. Unpaid refers to unpaid family workers. Regular employees receive salary or wages on a regular basis. Casual workers receive a wage according to the terms of the daily or periodic work contract. *Source:* NSS Employment and Unemployment Survey

[5] We always use the sampling weights provided. There is some question whether differences in sampling strategy between rounds might have a (slight) impact on the comparability of levels in the female labor force participation shown here, particularly also the peak reported in 2004–05. As discussed above, however, they will not affect the observation of low levels, and the stability over time. For a discussion of these issues, see Klonner and Oldiges (2014).

Marriage is almost universal in India, with average age at marriage around 19 in urban India in 2004–05 (Desai et al. 2010). According to the NSS survey data, the share of ever-married women among urban women age 25–54 was 95.3 percent in 2011 and 96.5 percent in 1987. Because in the age group 20–24 the marriage rate declined over time as more women pursue higher education and postpone marriage, we focus our analysis on women age 25 and older. We also exclude the 2 percent of all married women in this age group who report being head of their household.[6]

Female participation rates are calculated using women's reported usual status, which refers to a reference period of 1 year in which the principal activity is the activity in which the respondent spent the majority of time. Subsidiary activity status is recorded as well but is not taken into account in our analysis, as it affects less than 5 percent of the adult urban female population and its definition is not consistent over time.[7] Nonetheless, the pattern of female labor force participation is similar across different age groups, when including unmarried women, and when including labor force participation in both principal and subsidiary activities (see Table A1.1 in the appendix).

One might worry that even though unpaid family workers and own account workers are considered part of the labor force, women's work is underreported. Survey respondents may be reluctant to report women's contributions to family businesses or may not consider a woman's work to be different from her general domestic duties. This type of underreporting will mainly affect participation rates in rural areas, where women spent much more time on farm activities that are less likely to be considered as work, and will affect subsidiary status activities more than principal status activities because the former includes work done for only a few hours per day or during peak season only, etc. Principal status participation rates in urban India are arguably least

[6] We exclude them because we are interested in the role of women's own versus household head education, among others. Participation rates of female household heads are higher, and declined from 39 percent in 1987 to 30 percent in 2011.

[7] Before the 2004 wave, there was no lower bound on the number of hours spent on a particular activity to be considered as subsidiary activity, but in 2004 the minimum was set at 30 days of the reference year.

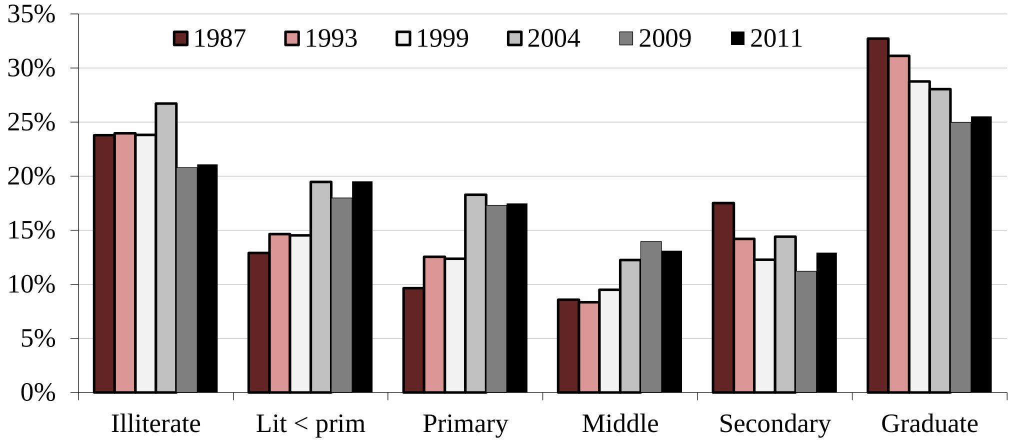
affected by underreporting of women's work but have the disadvantage that women working part time are not considered as active in the labor force if they spend the majority of their time in domestic duties. This is important to keep in mind, but as noted above this affects at most 5 percent of the sample and does not affect time trends.

To provide some verification of participation rates from the NSS Employment and Unemployment Survey using other data, we compare the 2004-05 numbers to the 2004-05 wave of the India Human Development Survey (Desai et al. 2009). There is no major time criterion to be considered as a worker in the IHDS survey, and there is considerably more probing as respondents are asked to specify each household member's contribution to each family business as well as any other activities earning an income or a wage.[8] For married women in urban India in the age group 25–54, the IHDS data show an employment rate (unemployment is not recorded) of 19.8 percent, which is very close to 19.6 percent based on the NSS data. The participation rate for married women in urban Delhi is also very similar between the NSS 2004–05 wave (19.4 percent) and a survey done for a study on women's work in 2006 (19 percent; see Sudarshan and Bhattacharya 2009).

Figure 2 shows that the urban FLFP rate has a U-shaped relationship with education and that the stagnation in FLFP hides a combination of rising participation among women with low education and a decline in participation rates of highly educated women. As income, wages, and access to different types of jobs are important candidates for explaining these patterns, we now turn to a brief discussion of those.

Figure 2: Urban female labor force participation rate by education level

[8] See http://ihds.umd.edu/questionnaires.html for the IHDS household questionnaires.



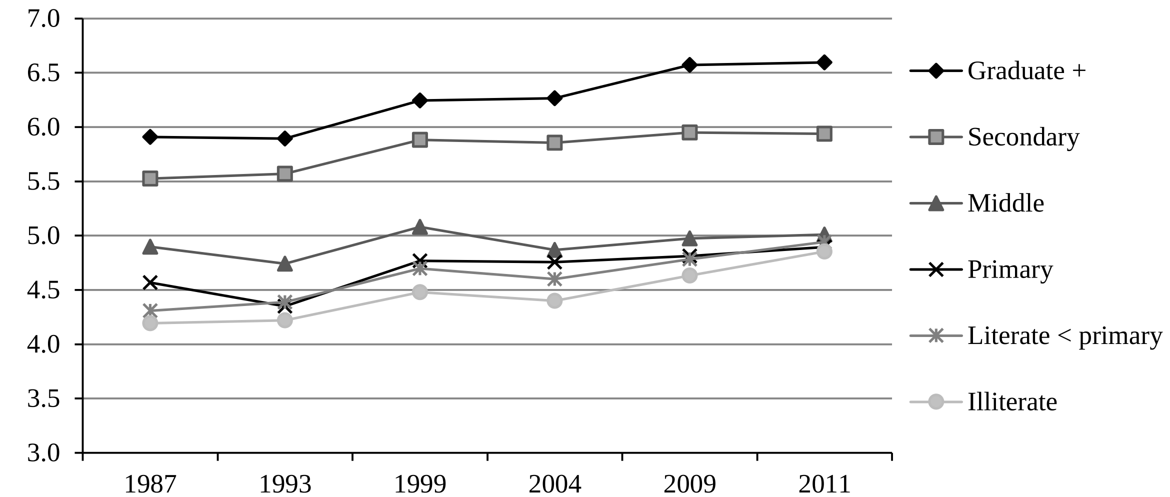
Note: Married women age 25-54. Education is the highest level completed, see appendix Table A1.2 for definitions. *Source*: NSS Employment and Unemployment Survey.

In line with India's high growth rates, earnings data form the NSS surveys show that real wages roughly doubled between 1987 and 2011 (see Fig. A1.1 in the appendix). In absolute terms, real wages increased almost equally for men and women, but the ratio of male to female average weekly earnings declined from 1.6 in 1987 to 1.3 in 2011. Given the very high participation rates of married men in this age group and their higher average wages, one can safely assume that most women in urban India are secondary earners. Rising earnings of men most likely had a strong negative impact on female labor force participation. But with women's wages increasing more than men's, positive substitution effects could at least partly offset the negative impact of men's income.

However, patterns in the data suggest there is no close link between women's wages and their labor force participation. Figure 3 shows women's real wages by education level. Returns to secondary and graduate education are high and rising, especially returns to graduate education. Real wages at lower levels of schooling, on the other hand, show a strong convergence due to relatively fast wage growth of illiterate women. If anything, own wage effects would thus have led to increases in labor force participation rates at both the ends of the educational distribution—for illiterate women on the one side and highly educated women on the other side. Going back to

Figure 2, however, we see that these are exactly the groups of women for whom participation rates declined.

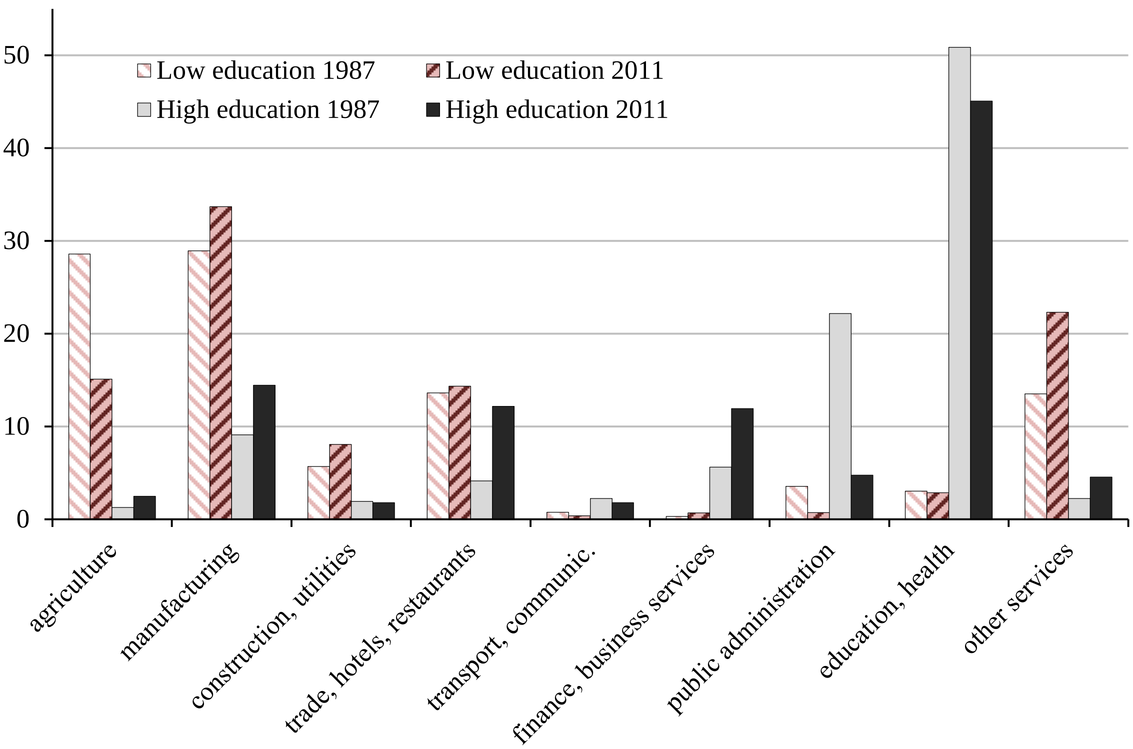
Figure 3: Log real wages for women age 25-54 by education level, urban India



Note: Wages are average total weekly earnings for casual and regular employees. Earnings are spatially deflated and in 1987-88 Rupees, based on the Labour Bureau Consumer Price Index for Industrial Workers and Deaton (2003). *Source*: NSS Employment and Unemployment Survey

Wages may have little impact on FLFP, despite rising returns to higher education, if employment growth in the activities appropriate for educated women is limited. As shown in Figure 4, the distribution of female workers across industries changes substantially with education. The distribution is shown separately for women below secondary education and those with secondary or higher education. Women with lower education work mainly in agriculture, manufacturing, and domestic services (included in “other services”). Access to white-collar services sector jobs is mostly confined to women with at least secondary education, but declined steeply over time. By and large, this pattern is consistent with the U-shape in education suggesting that only with at least secondary education, women gain access to jobs that are not subject to social stigma. It could also account for the declining participation rates of highly educated women whose supply increased much faster than available jobs, thereby reducing employment opportunities for them in these sectors.

Figure 4: Distribution of urban female workforce across industries, by education



Note: Distribution of female workers across industries, including employees, self-employed and unpaid family workers. Shares are in percentage of all female workers in the respective education group. Low education is below secondary schooling; high education is secondary or higher. *Source*: NSS Employment and Unemployment Survey.

In 1987 the vast majority of highly educated women worked in public administration, education, and health. This share declined to 50 percent in 2011, mainly driven by a declining share of public administration. Although financial and business services have become more important, they still account for only a small fraction of female employment. Consequently, highly educated women are increasingly working in industries such as manufacturing (mostly in textiles), wholesale and retail trade, and domestic services; within these sectors, many highly educated women work in professional and administrative occupations so that there are still white-collar occupations.[9] For low-educated women, employment has shifted from agriculture into food and tobacco, textiles, construction, and domestic services.[10]

The changing industrial distribution of workers is consistent with Boserup's (1970) description of white-collar jobs becoming increasingly scarce when education levels grow rapidly. The distribution of male workers (not shown) confirms that the share of white-collar services employment has declined not just for women but for the entire labor force, while employment growth has been concentrated largely in construction and retail and wholesale trade. At the same time, educational attainment has indeed grown rapidly. The share of women with at least secondary education grew from 21 percent in 1987 to 45 percent in 2011. Among men, this share increased from 38 to 56 percent over the same period (for more detail, see Fig. A1.2 in appendix 1). Besides rising incomes, this growing supply of highly educated workers combined with employment shifting toward less skill-intensive sectors could be an important reason why participation rates among highly educated women have declined.

III. Estimating the Determinants of Women's Labor Force Participation

Using the NSS survey data, we test how the different factors discussed above have contributed to the stagnation of FLFP in urban India. We first estimate the effect of education, income, and other variables on women's labor force participation in a reduced form labor supply model. In the next section, a decomposition analysis is used to show how changes in the explanatory variables

[9] Due to changes in the occupational classification used in the NSS data, we cannot construct a consistent definition of white-collar occupations over time. We do find that in all sectors, highly educated women are more likely to work in professional and administrative occupations than women with less than secondary education.

[10] Domestic services could be considered appropriate for women, but they are typically not covered by existing legislation and are relatively easy victims of exploitation due to their invisibility, lack of education and, often, migration background (NCEUS 2007).

and changes in coefficients and unobservables contributed to the stagnation of FLFP between 1987 and 2011.

The probability of woman *i* in year *t* (1987, 1999, 2004, 2009, and 2011)[11] being in the labor force (including self-employment, unpaid family work, regular and casual wage employment, and unemployment) is modeled as

$$P_{it} = F(\alpha_{st} + \sum_E \beta_t^E D_{it}^E + \beta_{Xt} X_{it} + \beta_{Zt} Z_{it}) \,, \tag{1}$$

where *F* is the standard normal cumulative distribution function. The model is estimated separately for each year to allow for changes in behavior over time.

The first right-hand side term is a state fixed effect. Education is measured through dummies for the highest education level completed, D^E (E=2, …, 6), with illiterate (E=1) as the reference level. X_{it} is a vector of explanatory variables at the individual and household level, including household income excluding her own earnings, and education of the household head. Income is measured as total household earnings in the reference week excluding the woman's own earnings.[12] We use income per capita to control for differences in the number of people depending on that income.[13] Instead of an asset index or similar measure of wealth, the education level of the household head is included to capture household wealth or permanent income beyond total earnings. If higher socioeconomic status leads to more restrictions on women and if greater wealth reduces the need for women to work, the education level of the household head should have a

[11] Data for 1993 are not used in the econometric analysis because the 1993 data do not contain district identifiers, which are needed to construct district-level explanatory variables. Districts are administrative units at the substate level in India. Our sample covers 362 districts across India's 18 main states.
[12] For total household earnings, the earnings of self-employed household members are imputed based on the earnings of employees. Although this is a fairly rough approximation, it appears this imputation serves the purpose of measuring household income well: results are very similar when households with at least one self-employed adult are excluded from the sample.
[13] Data on other income sources are not collected in the survey, nor are household assets.

strong negative effect on participation. We also control for the security of household income through an indicator for having at least one male household member with salaried employment.[14]

Further individual controls are age, age squared, number of children, and social group (indicators for scheduled caste and tribe – SCTS –, non-SCST Hindu, Muslim, and other). These caste and religion dummies are included to capture direct impacts of culturally or religiously determined restrictions on women, which are expected to be strongest among Muslim and high-caste Hindu households (Chen and Drèze 1992; Das and Desai 2003).

Z_{it} is a vector of local labor demand and supply variables, included to capture the effect of the availability of suitable or attractive jobs. We include the district share of male workers in agriculture[15], industry, construction, white-collar services (financial and business services, public administration, education, health, and social work), and other services; and the share of the district working age population with a graduate degree, to control for the local supply of high-skilled labor. We expect that female participation is higher in districts that are relatively specialized in white-collar services. The relative supply of graduates in the district is expected to depress participation rates through a crowding-out effect. These factors are expected to be particularly important for highly educated women.

Standard labor supply models would also include the woman's own wage, but identification of own-wage effects is challenging. To estimate the effect of wages on labor force participation it is necessary to use predicted wages for workers and non-workers, corrected for selection into employment and predicted based on at least one exogenous variable (for a discussion see Heim

[14] Households, especially in developing countries, can use women's labor supply to deal with negative income shocks or uncertainty (Attanasio et al. 2005; Bhalotra and Umaña-Aponte 2010). Implicit in the empirical model is the assumption that women's participation decision is made conditional on men's: we do not consider joint utility maximization or bargaining within the household. Given the very high and unresponsive labor force participation rates of men, we believe that this assumption is warranted.

[15] Employment shares are measured within urban areas of districts, but even in urban areas, households engage in agricultural and livestock production.

2007). Following leading studies in the literature (Blau and Kahn 2007; Heim 2007), we estimate two different specifications to identify the own-wage effect. One exploits wage variation across districts, the other exploits wage variation across state-age-education groups. The two sources of variation give very different estimates, which do not allow us to draw firm conclusions about the impact of wages on women's labor force participation. However, the estimated effects of other explanatory variables, including education, are robust to the different specifications and to excluding the own wage from the model.[16] Given the difficulties in identifying the own wage effect and the inability to include the self-employed in models that include own wages, we focus here on the results without including own-wage effects. Results for own-wage estimates and more details of the estimation method are discussed in appendix 2.

Table 1 contains sample means for all variables. The largest changes over time are increasing education (women's own education levels and those of their male partners and household heads, as well as the district population share with graduate level education) , fertility decline, and increasing household income. Further note that employment has shifted over time from agriculture, manufacturing, and white-collar services to construction and other services. To explore in more detail to what extent the determinants of labor force participation differ between low- and highly educated women, equation (1) is also estimated separately for women with less than secondary education and women with secondary or higher education.

Estimation Results

[16] The level of the own education effects does change but in all specifications we find a strong U-shape and a large decline in the effect of secondary and graduate education over time.

Estimation results are reported in Table 2 as average marginal effects, showing the change in the probability of being in the labor force associated with a unit change in the explanatory variable (for categorical variables this is the difference with the reference category). First of all, the U-shape in education appears even stronger in the marginal effects than in the average unconditional participation rates in Figure 2. Even conditional on variables that could have explained the unconditional U, such as partner's income and education, caste, or religion, participation declines as education increases up to intermediate levels.

Table 1. Sample Means

	1987	1999	2004	2009	2011
Labor force	0.18	0.18	0.20	0.17	0.18
Illiterate	0.42	0.32	0.28	0.23	0.22
Literate	0.11	0.08	0.07	0.07	0.07
Primary	0.15	0.12	0.13	0.12	0.11
Middle	0.11	0.14	0.16	0.15	0.15
Secondary	0.14	0.20	0.22	0.26	0.27
Graduate	0.07	0.13	0.14	0.17	0.18
Log income	3.63	3.99	4.08	4.36	4.47
Salaried employment	0.52	0.48	0.46	0.46	0.46
Hh head Illiterate	0.21	0.18	0.16	0.15	0.14
Hh head Literate < prim.	0.14	0.10	0.10	0.08	0.08
Hh head Primary	0.17	0.12	0.13	0.11	0.11
Hh head Middle	0.14	0.15	0.16	0.15	0.16
Hh head Secondary	0.22	0.26	0.28	0.30	0.29
Hh head Graduate	0.13	0.18	0.18	0.21	0.22
Hindu non-SCST	0.66	0.65	0.65	0.66	0.65
SCST	0.14	0.17	0.17	0.16	0.16
Muslim	0.14	0.14	0.14	0.14	0.15
Other social group	0.05	0.05	0.05	0.04	0.04
Age	35.6	36.1	36.6	36.7	36.8
Children 0–4	0.69	0.53	0.50	0.42	0.39
Children 5–14	1.59	1.37	1.20	1.05	1.05
Agriculture	0.07	0.06	0.05	0.05	0.05
Construction	0.07	0.10	0.10	0.12	0.12
Manufacturing	0.27	0.23	0.24	0.22	0.23
White-collar services	0.20	0.18	0.18	0.19	0.19
Other services	0.38	0.43	0.43	0.41	0.41

Graduate share	0.11	0.16	0.17	0.21	0.22
N	29031	32541	29513	27198	27306

Note: Averages for married women age 25–54, calculated using sampling weights.
Source: NSS Employment and Unemployment Survey

A remaining channel—one not captured in control variables—is through social stigma. It is possible that the stigma associated with low-skilled jobs (including in agriculture, menial jobs in manufacturing and construction, or in domestic services) increases as women attain low and intermediate levels of education. This means education is associated with an increased (fixed) utility cost of engaging in low-skilled work. This channel can also explain the upward sloping part of the education U-curve: once women attain secondary or post-secondary education, the utility cost disappears as they gain access to white-collar jobs that are not subject to social stigma. In all, the education U-curve conditional on income, social status, and the sectoral structure of employment (which we further discuss below) can be explained by social stigma associated with different types of jobs.

In addition, the positive effects of higher education could reflect higher wages or positive selection effects. As we find very similar estimates when controlling for the own wage, we think the own wage channel does not play an important role, despite high returns to education in the labor market. On the other hand, it is quite plausible that the positive higher education effect partly reflects an upward bias due to endogenous selection into higher education of girls with stronger labor market orientation. This would not only bias upwards the effects of higher education, but is also consistent with the large decline in the positive effects of secondary and graduate education over time. If increasing educational attainment has been driven by the growing supply of education, for example, highly educated women in 1987 were more positively selected than those in 2011. We cannot test this directly without modeling educational attainment itself, which is beyond the scope of this paper, but we provide suggestive evidence for a decline in positive selection in Section V.

Moving down in Table 2, we find a negative income effect as expected. Security of income (male salaried employment) also reduces women's labor force participation, and we find a particularly strong negative effect of education of the household head. The size of the effects declines over time, suggesting that women have become less responsive to income insecurity and to overall socioeconomic status of the household. Household head education effects remain, however, quantitatively large.

Table 2. Estimation Results (Average Marginal Effects)

Pr (Labor force)	**1987**	**1999**	**2004**	**2009**	**2011**
Own education (Ref. = Illiterate):					
Literate	-0.050***	-0.063***	-0.051***	-0.030**	-0.026*
	(0.009)	(0.011)	(0.013)	(0.014)	(0.014)
Primary	-0.072***	-0.074***	-0.062***	-0.025**	-0.027*
	(0.008)	(0.011)	(0.015)	(0.012)	(0.014)
Middle	-0.067***	-0.084***	-0.100***	-0.060***	-0.064***
	(0.011)	(0.009)	(0.013)	(0.013)	(0.011)
Secondary	0.086***	-0.020*	-0.048***	-0.056***	-0.041***
	(0.013)	(0.010)	(0.014)	(0.014)	(0.014)
Graduate	0.324***	0.217***	0.144***	0.131***	0.151***
	(0.020)	(0.018)	(0.023)	(0.019)	(0.022)
Log income	-0.034***	-0.017***	-0.032***	-0.028***	-0.022***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Male salaried emp.	-0.022***	-0.032***	-0.019**	0.002	-0.005
	(0.007)	(0.008)	(0.009)	(0.009)	(0.010)
Household head education (Ref. = Illiterate):					
Literate	-0.067***	-0.045**	-0.040**	-0.025	0.017
	(0.012)	(0.020)	(0.017)	(0.018)	(0.019)
Primary	-0.107***	-0.078***	-0.053***	-0.035**	-0.057***
	(0.012)	(0.012)	(0.015)	(0.014)	(0.018)
Middle	-0.126***	-0.115***	-0.078***	-0.072***	-0.083***
	(0.013)	(0.011)	(0.014)	(0.014)	(0.015)
Secondary	-0.170***	-0.150***	-0.121***	-0.095***	-0.103***
	(0.013)	(0.013)	(0.014)	(0.015)	(0.015)
Graduate	-0.166***	-0.154***	-0.110***	-0.084***	-0.126***
	(0.016)	(0.014)	(0.018)	(0.017)	(0.019)
Social group (Ref. = Hindu non-SCST):					
SCST	0.089***	0.054***	0.036***	0.059***	0.033***

	1987	1999	2004	2009	2011
	(0.010)	(0.011)	(0.013)	(0.014)	(0.009)
Muslim	-0.058***	-0.069***	-0.086***	-0.087***	-0.082***
	(0.010)	(0.010)	(0.014)	(0.012)	(0.011)
Other	0.021	0.013	0.004	0.022	0.039**
	(0.015)	(0.017)	(0.013)	(0.015)	(0.018)
Age	0.020***	0.026***	0.027***	0.016***	0.014***
	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)
Age^2	-0.0003***	-0.0003***	-0.0004***	-0.0002***	-0.0002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Continues on next page.

Table 2 continued

Pr (Labor force)	**1987**	**1999**	**2004**	**2009**	**2011**
Children 0–4	-0.022***	-0.018***	-0.024***	-0.036***	-0.039***
	(0.004)	(0.004)	(0.005)	(0.007)	(0.008)
Children 5–14	-0.005**	-0.001	0.008**	-0.003	0.007*
	(0.003)	(0.002)	(0.004)	(0.004)	(0.004)
District male employment shares (Ref. = construction):					
Agriculture	0.255*	0.171*	0.165	-0.008	0.220**
	(0.132)	(0.097)	(0.116)	(0.108)	(0.096)
Manufacturing	0.073	-0.097	-0.039	0.155*	0.268***
	(0.118)	(0.087)	(0.099)	(0.091)	(0.077)
Services	-0.048	-0.090	-0.015	0.120	0.014
	(0.121)	(0.084)	(0.093)	(0.088)	(0.073)
White-collar serv.	-0.036	-0.022	-0.086	0.170	0.052
	(0.124)	(0.099)	(0.120)	(0.106)	(0.100)
District grad. share	0.004	-0.087	0.017	-0.402***	-0.051
	(0.111)	(0.083)	(0.105)	(0.091)	(0.082)
N	29031	32541	29513	27198	27306
Pseudo R2	0.145	0.126	0.125	0.114	0.097
FLFP rate	0.185	0.179	0.203	0.174	0.179

Note: Married women age 25–54. All estimations include state fixed effects. District-clustered standard errors in parentheses, *** $p < .01$, ** $p < .05$, * $p < .10$.

Looking at the social group variables, we find that women in SCST households are most likely to work, but the gap between SCST and non-SCST Hindus declined.[17] The impact of religion

[17] From 1999 onwards, the NSS data also distinguish Other Backward Class (OBC) households. Including a separate category for OBC—rather than including them in the reference non-SCST group—we find that OBC women have higher FLFP than high caste Hindus in 1999 and 2004, but there is no difference in 2009 and 2011. The estimated gap between SCST and high caste Hindus is somewhat larger but still declines over time.

appears stronger, with Muslim women 6 to almost 9 percentage points less likely to work than non-SCST Hindus; a difference close to half the female labor force participation rate.

Women's age and the presence of children in the household have the expected effects. Participation first increases and then declines with age. We see that the age profile shifted somewhat after 2004, reducing the peak age from around 40 in 1987–2004 to around 35 years in 2011. At the same time, the negative effect of young children almost doubled in magnitude. Though the estimates cannot be interpreted as causal due to joint fertility and participation decisions, we clearly see an increasing negative association between women working and the presence of young children in the household.

The bottom of the table shows the estimated effects of district demand and supply variables.[18] We do not find that local supply of high-skilled workers affects FLFP much, except for a strong negative effect in 2009. This could reflect the impact of the global financial crisis, which led to substantial declines in employment (see for example Kucera et al., 2012). Regarding the sectoral structure of employment, in 1987 and 1999 FLFP was highest in districts where agriculture makes up a higher share of urban employment suggesting that agricultural activities in and at the fringes of cities generate higher employment opportunities for women. Manufacturing has started drawing in more women since 2009. Surprisingly, the employment shares of white-collar services and other services are not significantly positively related to FLFP.

Subsample estimates (reported in Tables A1.3 and A1.4 in the appendix) shed more light on this. In the low-education sample, we see the strong association of FLFP with agricultural employment in the early years and again in 2011. This same pattern is not present for highly educated women. The negative effect of high-skilled labor supply is much stronger in the high-

[18] If we replace the district-level variables and state fixed effects by district fixed effects, results are virtually unchanged. These results are available on request.

education sample, where it remains significantly negative (though smaller in magnitude) in 2011. We also find a positive effect of white-collar services in the high-education sample, but it is significant only in 2009. It appears that 2009 was characterized by fiercer competition for skilled jobs, and only districts with a large share of employment in white-collar services could keep highly educated women in the labor force. By 2011, the crowding out effect is weaker and at the same time, highly educated women are shifting more toward the manufacturing sector, similar to the low-education sample.

There are other important differences between the two education groups. First of all, the negative income effect in the high-education sample halves between 1987 and 2009 and disappears in 2011, as opposed to a slight increase in the low-education sample. Second, education of the household head has a strong negative effect in the low-education sample, but no effect on highly educated women in any of the years. Third, male salaried employment—our proxy for income security—is associated with lower labor force participation of women with low education, while the opposite is found for highly educated women (though for both subsamples, the effect declines in magnitude and is no longer statistically significant in 2011). These results suggest that highly educated women are less constrained by family circumstances in their labor force participation decision, while women with less than secondary education appear to be boxed in by necessity to work if household incomes are very low or insecure, and stigmas attached to working if they have some education and are in more secure economic environments. The finding that manufacturing employment is nowadays associated with higher FLFP is an indication that manufacturing jobs are becoming less stigmatized.

Regarding changes in participation rates over time, it follows from the probit estimates that the increase in women's educational attainment and fertility decline should have translated into higher labor force participation. Working in the opposite direction, however, is the increase in educational attainment of men and the increase in male incomes. Changes in the structure of employment also appear to have contributed to lower participation rates. The employment shares of agriculture, manufacturing, and white-collar services declined, while these are the sectors positively associated with FLFP. The decomposition analysis in Section IV quantifies the contributions of changes in the different covariates included in the model. Before turning to those results, we first discuss the potential influence of migration on our estimation results.

The Potential Role of Rural-Urban Migration

Rural to urban migration is an important part of India's development process. The population numbers in appendix table A1.1 show that the total female population grew by 50 percent in the period 1987-2011, comprising a 91 percent growth of females in urban India and 38 percent growth in rural India. Rural-urban migrants are typically not a random selection of the rural population, so one might worry that the stagnation of urban FLFP and the changes in labor force participation determinants are driven by the inflow of migrants.

The National Sample Survey Organisation (NSSO) integrated the collection of migration data with the employment surveys in 1987 and 1999 but not with those of 2004 and after. In 1987 and 1999, almost 70 percent of women in our sample have a migration background, of which almost 60 percent (i.e., around 40% of the total female urban sample) migrated from a rural area. The most important reason for migration is marriage (about 65 percent of all female migrants). On average, rural-urban migrants are more likely to be at either end of the education distribution (illiterate or with at least secondary education) than nonmigrants, and less likely to have low or intermediate educational attainment (see Fig. A1.3 in the appendix). Given the U-shaped relationship between education and labor force participation, the compositional impact of migration should have been to increase urban FLFP, if anything. But despite the large share of migrants and differences in educational attainment, controlling for rural-urban migration background in the 1987 and 1999 estimations has no impact on the results. The migrant variable itself has no significant effect on labor force participation. Results are also unchanged if we add dummies for both the woman's and her spouse's migration background and their interaction, which captures the difference between women migrating to join their husbands' family versus families migrating jointly. Even if we drop all rural-urban migrants from the sample, the results do not change.[19]

Unfortunately, no migration data was collected in the employment surveys after 1999, but the NSSO does provide descriptive statistics on migrants from a special migration survey conducted in 2007–08 (NSSO 2010). Based on these statistics we find that the educational attainment differences between urban female migrants and the total urban female population have been quite stable between 1987–88 and 2007–08. In other words, the educational composition of female migrants has not changed differently from the educational composition of the entire urban female population. We are therefore fairly confident that changes in female migration patterns are not driving the stagnation of FLFP.

IV. Decomposition Analysis

In order to quantify the contribution of different explanatory variables to the observed change—or lack thereof—in the female labor force participation rate, we now turn to a decomposition analysis, using the probit estimates for 1987 and 2011. Following Fairlie's (2006) extension of the Oaxaca-Blinder decomposition (Blinder 1973; Oaxaca 1973), the labor force participation equation (Eqn. 1) is expressed as $Y_i^t = F(X_i^t \beta^t)$, resulting in the following decomposition:

$$\bar{Y}^{11} - \bar{Y}^{87} \approx \left[\sum_i^{N^{11}} \frac{F(X_i^{11}\beta^{87})}{N^{11}} - \sum_i^{N^{87}} \frac{F(X_i^{87}\beta^{87})}{N^{87}}\right] + \left[\sum_i^{N^{11}} \frac{F(X_i^{11}\beta^{11})}{N^{11}} - \sum_i^{N^{11}} \frac{F(X_i^{11}\beta^{87})}{N^{11}}\right]. \quad (2)$$

[19] Detailed results for this section are available on request.

The N^t are sample sizes and $\bar{Y}^t$ the sample average probability of being in the labor force.[20] The first right-hand side term in (2) measures the contribution of changes in covariates, evaluated at 1987 coefficients. It measures how changes in covariates would have translated into changes in FLFP if coefficients and unobservables had remained at their *start-of-period* (1987) levels. The second term is the remaining change, which measures the change in FLFP that would have resulted from changes in coefficients and unobservables if covariates had been constant at their *end-of-period* (2011) levels.

The contribution of a single explanatory variable is computed using a counterfactual predicted participation rate, by replacing only this particular variable, say X_{1i}^{87}, by its 2011 counterpart X_{1i}^{11}, while keeping all other variables at their 1987 values. This is done by drawing a 2011 subsample of size equal to the 1987 sample, matching women on their predicted probability of working (based on a pooled probit estimation), and assigning women in the 2011 subsample the value of X_1 observed for their 1987 match. The results reported below are based on 1000 random subsamples, in which furthermore the order of variables is randomized to account for the fact the contribution of one variable depends on the value of other variables.[21]

The decomposition analysis can also be carried out with covariate contributions measured at 2011 coefficients, and coefficient contributions measured at 1987 covariate levels, using the following expression:

$$\bar{Y}^{11} - \bar{Y}^{87} \approx \left[\sum_i^{N^{11}} \frac{F\left(X_i^{011}\beta^{11}\right)}{N^{11}} - \sum_i^{N^{87}} \frac{F\left(X_i^{87}\beta^{11}\right)}{N^{87}}\right] + \left[\sum_i^{N^{87}} \frac{F\left(X_i^{87}\beta^{11}\right)}{N^{87}} - \sum_i^{N^{87}} \frac{F\left(X_i^{87}\beta^{87}\right)}{N^{87}}\right]. \quad (3)$$

If coefficients and covariates changed substantially from 1987 to 2011, which is the case for a number of variables, measured contributions will differ between (2) and (3). We therefore report

[20] The equality in equation (2) does not hold exactly for the probit model, because the average value of predicted probabilities does not equal the average of the dependent variable. It is a close approximation, however, and we find very similar results when we use a logit model instead (for which the equality does hold exactly, see Fairlie [2006]).
[21] See Fairlie (2006) for a more detailed discussion of the method.

results for both choices of reference year. The "true" contribution of a variable will lie somewhere in between, and of course this type of decomposition is an accounting exercise, ignoring the fact that changes in covariates and changes in coefficients are interdependent.

Table 3 shows the decomposition results. In our sample of married women 25–59, the female labor force participation rate declined by 0.6 percentage points between 1987 and 2011. At 1987 coefficients (Eqn. 2), covariate changes account for a 0.3 percentage point decline. The remaining 0.2 percentage point is accounted for by changes in coefficients and unobservables. At 2011 coefficients (Eqn. 3), we find a much larger negative contribution from covariate changes, which is almost entirely offset by a large positive contribution from changing coefficients and unobservables.

Table 3. Decomposition of FLFP, 1987–2011

Pr (labor force) 1987	0.185	(N=29031)		
Pr (labor force) 2011	0.179	(N=27306)		
Difference	-0.006			
	At 1987 coefficients		At 2011 coefficients	
	Contribution	SE	Contribution	SE
Own education	0.047***	0.003	0.011***	0.003
Log income	-0.030***	0.002	-0.020***	0.003
Male salaried emp.	0.001**	0.000	0.000	0.000
Education household head	-0.025***	0.002	-0.021***	0.002
Caste and religion	0.001***	0.000	0.000	0.001
Age	0.001***	0.000	0.000	0.001
Children	0.009***	0.001	0.007**	0.003
District employment shares	-0.011***	0.003	-0.019***	0.004
District graduate share	0.001	0.008	-0.006	0.007
State dummies	0.003***	0.001	0.003***	0.001
Total covariates	-0.003		-0.045	
Coefficients & unobservables	-0.002		0.039	

Note: SE = standard error. *** $p < .01$, ** $p < .05$.

The variable-specific covariate contributions show that the increase in women's education levels and declining numbers of children account for an increase in participation rates.[22] These effects are offset, however, by negative contributions from rising household incomes, education of household heads, and the change in the sectoral structure of employment. The probit estimation results indicated that only agricultural and manufacturing employment are associated with significantly higher female labor force participation rates, but both sectors' shares in employment declined over time. This sectoral change alone can account for a 1 to 2 percentage point reduction in FLFP. The negative contributions of household income and household head education are larger, but because women have become less responsive to income and household head education, they account for a smaller decline in FLFP at 2011 coefficients than at 1987 coefficients.

The total covariate contribution is negative and much larger at 2011 coefficients. Sensitivity with respect to the choice of reference year is mainly due to the contribution of women's education: at 1987 coefficients, increasing education accounts for an increase in FLFP of 4.7 percentage points, while at 2011 coefficients the contribution is only 1.1 percentage points. This implies that FLFP would have increased by 3 percentage points (rather than decline by 0.6 percentage points) if educational attainment had increased without the effect of education declining. The remainder of this paper is devoted to a further analysis of precisely this declining effect of higher education.

V. The Declining Effect of Higher Education on Labor Force Participation

As discussed in Section III, the effect of higher education on women's labor force participation could partly reflect an upward selection bias, where completing education and joining the labor

[22] The positive contribution of state dummies suggests that growth of the urban female population was higher in states with higher FLFP rates. This could be due to migration: either migration from low-FLFP states to high-FLFP states, or stronger urbanization within high-FLFP states.

force are both outcomes of some unobservable determinants. Examples of such unobserved determinants could be the education or labor force participation of mothers, influences of peers, or a more general preference for work that motivates both higher education and labor force participation. This selection effect might change over time. If the average woman completing secondary or higher education in 2011 is less positively selected than her 1987 counterpart, this could potentially account for the declining effects of secondary and graduate education between 1987 and 2011.[23] A detailed analysis of the determinants of women's educational attainment would require data on women's parental background and on schooling supply and other characteristics of the location where they grew up. Unfortunately, those data are not available, as we only observe married women in their husband's household—which is often in a different area than where they grew up—and have no information on their location of origin or on their parents' education and employment. The following section provides supporting evidence, however, for the empirical relevance of the selection channel, which is also consistent with an analysis by cohorts we discuss next.

Among the factors that could explain a decrease in positive selection are the increasing supply of education and rising marriage market returns to education: both would be reasons for women to pursue more education even in absence of expected labor market returns and unrelated to the unobservable propensity to join the labor force. Given the high pace of expansion of schooling supply, it is likely that highly educated women in 2011 are less positively selected than highly educated women in 1987.[24]

[23] Another explanation would be a decline in the quality of education. Azam and Kingdon (2013) study gender bias in education expenditure and show that in the period 1993–2005, when girls' education caught up to boys', households still spent less on girls, primarily by sending girls to public schools and boys to private schools. Girls are thus likely to receive lower quality schooling than boys, even if they attain the same level of education. Unfortunately we do not observe the type of institution a woman attended or any other indicator of the quality of education in the NSS data.

[24] As discussed in Section 2 some recent studies show that (girls') enrollment responds to the growth of jobs in IT and IT enabled services (Jensen 2012; Shastry 2012; Oster and Millett Steinberg 2013), but this is a very recent development and this sector still accounts for a very small share of employment. We are not aware of any research on

Besides an expansion in the supply of education, rising marriage market returns to women's education could be driving women to pursue higher education. Marriage is of great importance in India, especially to women and their parents (Anderson 2003), as women typically leave their parental household and migrate to live with their husband's family (see Rosenzweig and Stark 1989; Banerjee et al. 2013). Despite a growing literature on women's earnings capacity and their bargaining power within marriage in developing countries (e.g. Luke and Munshi 2011), there is little evidence on the marriage market returns to women's education. According to Anderson (2003), the most important quality of women on the marriage market in India is a good appearance, while for men their ability to earn a living is most important. Data for India in Banerjee et al. (2013) show both men and women have a preference for marrying a highly educated spouse, though their sample includes only educated persons from the urban middle-class in West Bengal. Rising labor market returns to education would be an obvious reason why men prefer more educated women. However, even in absence of labor market returns, women's education can contribute to husbands' social status directly and through higher productivity in status production (Eswaran et al. 2013). Another important channel could be increased productivity of maternal time in the production of child human capital (Lam and Duryea 1999), which raises the demand for educated wives if labor market returns to men's education increase (Behrman et al. 1999).

In Klasen and Pieters (2013) we show that marriage market returns to education became significantly more convex between 1987 and 2009. In 2009 women needed at least secondary education to have a reasonable chance of marrying a highly educated and high-earning spouse. In contrast, primary school and certainly middle school generated reasonable odds to attract a high-

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the causal effect of education on women's labor force participation in India or on the impact of rapidly increasing schooling supply on women's educational attainment, other than evaluations of recent policies and programs for primary education and a growing literature on higher education quota for low-caste men and women (e.g., Bertrand et al. 2010; Kingdon 2007).

quality spouse in 1987. This is consistent with our claim that at least some of the female education expansion is driven by expected marriage market returns rather than labor market returns.

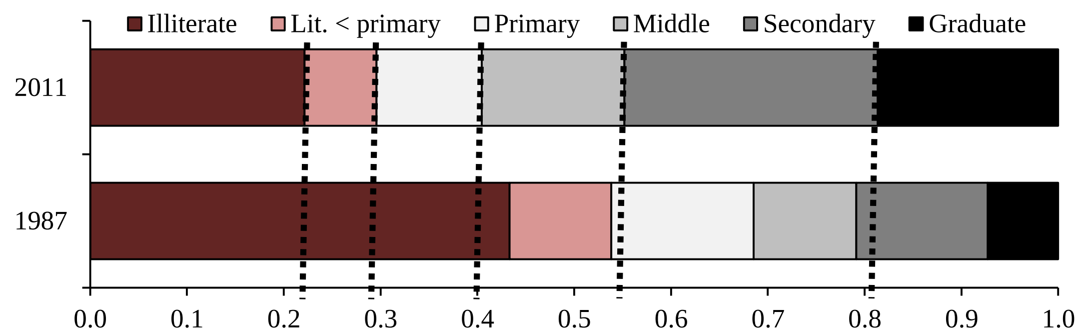
Selection Bias in the Effects of Education

Without instruments for educational attainment we cannot control for selection into education, but the extreme case—assuming that the education effects capture endogenous selection only—can be used to estimate an upper bound on the contribution of changes in selection to changes in the estimated effects of education. For simplicity, suppose there is one unobservable characteristic that determines labor force participation, and let us call this *ability*. Assume there is perfect sorting on ability into education, the ability distribution in the population is fixed, and there are k different ability levels in the population with $k = 1, \ldots, 6$ (one could also think of a uniform distribution of ability, but the idea remains the same). We thus have six ability types with corresponding ability level a^k, increasing in k.

Taking 1987 as our benchmark year, the 1987 distribution of education ($E = 1, \ldots, 6$) corresponds one-to-one with the distribution of ability types in the female population, such that $\alpha_{87}^{E} = a^k$ for $E = k$. As the supply of education expands, women end up with increasingly higher educational attainment, but the average ability of women at education levels E>1 declines over time. In other words, between 1987 and 2011, low-ability types move into higher education levels.

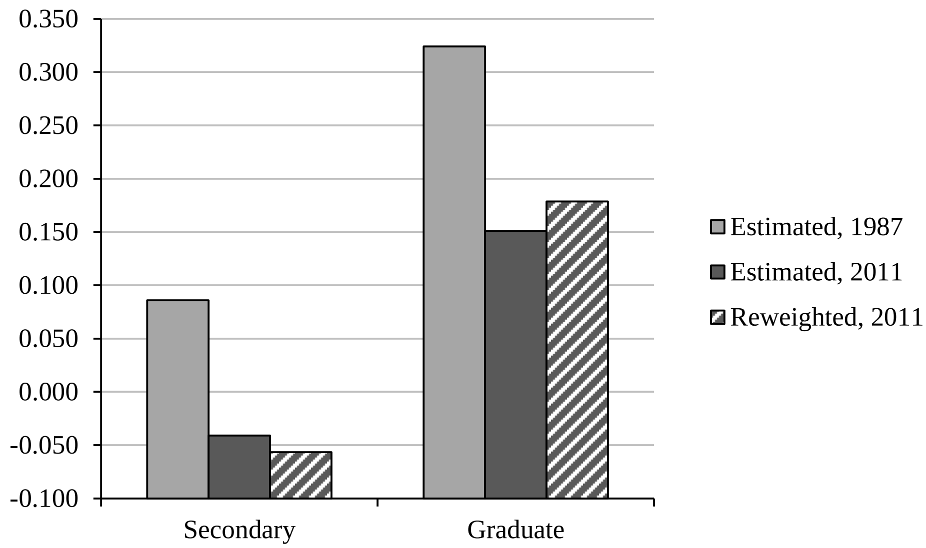
The shift is illustrated in Figure 5: by definition, illiterate women in 1987 are of ability level a^1, which is the ability level of the bottom 42 percent of the distribution. Literate women below primary school in 1987 are of ability level a^2, women with primary schooling in 1987 are of ability level a^3, and so on. By 2011, all literate women without or with primary schooling are of ability level a^1, as they all fall within the bottom 42 percent of the distribution. Similarly, all women with middle school completed in 1987 are of ability level a^4, but their 2011 counterparts are of ability levels a^1, a^2 and a^3; and so on for higher education levels. Thus average ability declines at all education levels above illiteracy.

Figure 5: Women's educational attainment in urban India



Note: distribution of married women age 25-54 across levels of educational attainment in 1987 and 2011. Source: NSS Employment and Unemployment Survey

Figure 6: Estimated and reweighted marginal effect of education, 1987 and 2011



Note: see Table A1.5 in the appendix.

Now assume that the estimated marginal effects of education on women's labor force participation measure the pure ability-selection effect. The 1987 education effects β_{1987}^{E} quantify the effect of ability on labor force participation for each ability type *k*. The education effects in other years should differ from those in 1987 only by the change in the ability composition of education groups. That is, they are a weighted average of the 1987 estimates. Table A1.5 in the appendix shows the original estimated marginal effects of education in columns 1–5, and the reweighted effects for 1999, 2004, 2009, and 2011 in columns 6 – 9. Results for secondary and graduate education are summarized in Figure 6.

As Figure 6 shows, the reweighting exercise predicts the change in the marginal effects of education from 1987 to 2011 quite well. While this is by no means conclusive evidence that the education effects are largely driven by selection,[25] it does show that declining selection could potentially play a large role in the declining effect of higher education on female labor force participation, where declining selection means that women's selection into education is increasingly based on characteristics that are not positively related to labor force participation.

Cohort Analysis

In a sample of women aged 25 to 54, educational attainment changes over time primarily because younger cohorts enter the sample with higher educational attainment while older cohorts with lower educational attainment age out of the sample. Consequently, the educational attainment by age group increases continuously, while the age composition of the sample is stable over time. To further probe the selection channel discussed above, we estimate age-group-specific marginal effects of education on labor force participation. If the declining effect of higher education indeed

[25] If purely selection-driven, one would not find negative estimates at intermediate education levels.

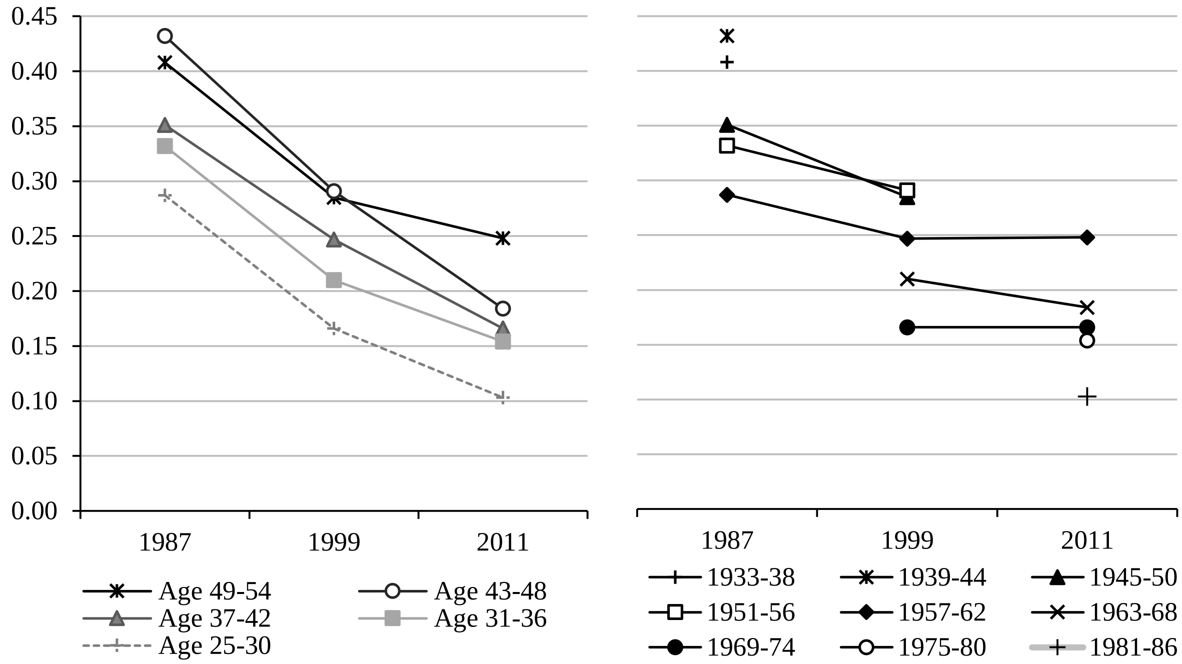
reflects a weaker positive selection into higher education among younger cohorts, we should observe that the effect of education is lower for younger women than for older women in a given year. Furthermore, we should find that the effect declines over time for a given age group (e.g., as 30-year old women in 2011 went to school more recently than 30-year old women in 1987) but not for a given birth-year cohort (e.g., those born in 1970).

For this analysis we use five 6-year age groups, which allows us to trace birth cohorts between the surveys in 1987, 1999, and 2011. The age group specific effects of education are estimated by including interaction effects of age group and education level in the probit specification (Eqn. 1) and calculating marginal effects of education for each age group. Figure 7 summarizes the results graphically, plotting the marginal effects of graduate education across survey years, by age group in panel (a) and by birth-year cohort in panel (b).[26] Full results are available in Table A1.6 in the appendix.

Figure 7: Marginal effect of graduate education by age group and birth-year cohort

(a) age groups **(b) birth-year cohorts**

[26] Marginal effects in nonlinear models vary with the value of other explanatory variables. For interaction terms, this variation is typically large. Effects can range from significantly negative to significantly positive, so the average marginal effect does not necessarily convey anything meaningful (see Ai and Norton 2004). We find that the marginal effects of graduate education are always positive. Effects are statistically significant only for the oldest two age groups (i.e., the effect of education is significantly larger for the two oldest groups than for the youngest group). For reasons of space we report only the averages, but detailed results are available from the authors.



Note: Estimated marginal effects of graduate education, see appendix table A1.6.

These results are in line with the selection channel driving the effect of graduate education: the marginal effect is lower for younger age groups than for older age groups in a given year. Furthermore, for each age group, the effect declines by about one third over time in each of the two 12-year periods. Looking at the same results presented by birth-year cohort in panel (b), we see some decline in the effect of graduate education over time in those cohorts we can trace, but the changes are much smaller.[27]

All in all, this is further supporting evidence that declining positive selection is a plausible explanation why graduate education has become less positively associated with women's labor force participation in urban India.

[27] For secondary education, the pattern is similar but somewhat less clear than for graduate education (see Table S1.5).

VI. Conclusions

In this paper, we investigate the very low and stagnating female labor force participation rates in urban India over the past 25 years. This stagnation is surprising given that it took place at a time of high GDP and earnings growth, a sizable fertility decline, a rapid expansion of female education, and rising returns to education. A combination of demand and supply side effects appear to have played a role in accounting for this stagnation. On the supply side, rising male incomes and education have reduced female labor force participation, showing that the classic income effect is at work in urban India. The effect of rising female education on female labor force participation is more complicated. While the pure shift toward increasing the proportion of women with graduate education has increased labor force participation, this effect is moderated and counteracted by range of opposing effects. First, the strong conditional U-shape pattern of the effect of education on labor force participation suggests that, particularly in the middle of the education distribution, other factors depress female labor force participation. This is most likely a result of stigmas for these women to be working in low-skilled sectors. But it appears that the role of stigma, at least towards working in the manufacturing sector, has started to decline in 2009, when the manufacturing sector has started to draw women into the labor force. Second, the positive effect of secondary and graduate education on female labor force participation has fallen considerably. We show supporting evidence that this is related to a declining positive selection into higher education. So even though more women have attained higher education, positive selection effects have been diluted, contributing to falling labor force participation rates among the highly educated.

Demand side changes also play a role. Changes in the sectoral structure of employment contributed to a reduction in FLFP rates. Most employment growth occurred in construction and low-skilled services, while expansion of employment in manufacturing and white-collar services has not been sufficient for absorbing a growing female working-age population.

These results suggest that, if current trends and preferences persist, there is little likelihood that women will drastically increase their labor force participation rates in coming years. Although employment growth in manufacturing has the potential to contribute to rising FLFP, India is, on current trends, unlikely to fully reap the benefits of the demographic dividend associated with its high share of the working-age population. And importantly, rising education of women will not contribute much to their economic empowerment, which is typically associated with employment and earnings. As such, the sustainability of India's high growth is very much in question if it fails to substantially improve the integration of educated women into the labor force.

It is difficult to make any definitive judgments on welfare effects. To the extent women's labor force participation is decided by their families and does not reflect women's own preferences, or is constrained by their inability to migrate for employment, policy action to promote female employment would be warranted. But even if the main constraint is women's own preferences, the degree to which this impedes their labor force participation should be a concern to policy makers. Our findings point at the importance of mismatches between the sectoral structure of employment and women's preferences. Employment growth in urban India has been concentrated in construction and low-skilled services, but from the perspective of female labor force participation a different growth strategy would be warranted; a more female-intensive export-oriented growth strategy (as has been pursued in many East Asian economies as well as in neighboring Bangladesh) would substantially increase female employment opportunities for those in the middle and even the top of the education distribution.

On the supply side, policies explicitly promoting the acceptability of female employment outside the public sector, policies to allow a greater compatibility of female employment with domestic responsibilities and policies to improve the safety of female workers in the private sector could also draw more women into the workforce.

Looking beyond India, the results could also hold considerable relevance for other parts of the developing world. In particular, in neighboring Pakistan as well as many countries of the Middle East and North Africa, substantial growth, fertility decline, and an expansion of female education also coexist with very low female labor force participation rates (e.g., World Bank 2003; Gaddis and Klasen 2014). The insights from this paper might also inform research and policy-makers in those settings.

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Appendix 1

Table A1.1: Female population and labor force by year, sector, and age group (in millions)

Urban		1987	1993	1999	2004	2009	2011
All ages	Population	88.9	109.7	125.3	136.5	155.8	170.0
	Labor force (ps)	11.5 (0.13)	14.5 (0.13)	15.8 (0.13)	20.2 (0.15)	20.0 (0.13)	22.8 (0.13)
	Labor force (ps+ss)	14.4 (0.16)	18.1 (0.16)	18.5 (0.15)	24.3 (0.18)	22.8 (0.15)	26.3 (0.15)
Age 15-64	Population	53.7	69.0	80.2	90.8	107.9	118.3
	Labor force (ps)	10.8 (0.20)	13.7 (0.20)	15.0 (0.19)	19.4 (0.21)	19.6 (0.18)	22.2 (0.19)
	Labor force (ps+ss)	13.4 (0.25)	17.1 (0.25)	17.5 (0.22)	23.3 (0.26)	22.2 (0.21)	25.7 (0.22)
Age 25-54	Population	31.1	41.1	49.0	55.9	67.1	74.1
	Labor force (ps)	7.1 (0.23)	9.5 (0.23)	10.8 (0.22)	13.9 (0.25)	14.3 (0.21)	16.6 (0.22)
	Labor force (ps+ss)	8.9 (0.28)	11.9 (0.29)	12.6 (0.26)	16.5 (0.30)	16.3 (0.24)	19.2 (0.26)
Rural		1987	1993	1999	2004	2009	2011
All ages	Population	309.5	339.3	377.1	408.9	423.4	427.6
	Labor force (ps)	77.9 (0.25)	80.4 (0.24)	88.0 (0.23)	102.0 (0.25)	87.9 (0.21)	77.4 (0.18)
	Labor force (ps+ss)	101.5 (0.33)	112.1 (0.33)	113.2 (0.30)	136.2 (0.33)	112.2 (0.26)	108.0 (0.25)
Age 15-64	Population	178.2	202.7	223.2	249.8	271.3	276.2
	Labor force (ps)	71.6 (0.40)	74.4 (0.37)	82.6 (0.37)	97.0 (0.39)	84.0 (0.31)	74.1 (0.27)
	Labor force (ps+ss)	92.1 (0.52)	104.0 (0.51)	106.4 (0.48)	129.3 (0.52)	107.1 (0.39)	103.6 (0.37)
Age 25-54	Population	104.4	121.3	135.3	152.0	167.0	169.5
	Labor force (ps)	47.0 (0.45)	49.8 (0.41)	57.4 (0.42)	68.3 (0.45)	60.6 (0.36)	54.2 (0.32)
	Labor force (ps+ss)	60.0 (0.57)	69.9 (0.58)	74.0 (0.55)	90.4 (0.59)	77.3 (0.46)	75.4 (0.44)
Total, all ages		1987	1993	1999	2004	2009	2011
Female	Labor force (ps)	89.4 (0.22)	94.9 (0.21)	103.8 (0.21)	122.2 (0.22)	107.9 (0.19)	100.2 (0.17)
Male	Labor force (ps)	227.4 (0.53)	262.5 (0.55)	284.4 (0.54)	316.2 (0.55)	340.3 (0.55)	347.5 (0.55)

Note: Numbers in millions, labor force participation rates are in parentheses. Labor force (ps) refers to principal status workers, (ps+ss) refers to principal and subsidiary status. *Source*: NSS Employment and Unemployment Surveys, with total population from the World Bank World Development Indicators.

Table A1.2: Definition of education levels

Illiterate below primary	Not literate
Literate	Literate without formal schooling or below primary level
Primary	Completed primary education
Middle	Completed middle school
Secondary	Completed secondary or higher secondary schooling
Graduate	Graduate or post-graduate degree

Table A1.3: Estimation results (average marginal effects) low-education subsample

Pr(Labor force)	**1987**	**1999**	**2004**	**2009**	**2011**
Own education (Ref. = Illiterate):					
Literate	-0.050***	-0.068***	-0.048***	-0.030**	-0.026*
	(0.010)	(0.012)	(0.014)	(0.014)	(0.014)
Primary	-0.071***	-0.076***	-0.058***	-0.019	-0.022
	(0.009)	(0.012)	(0.016)	(0.014)	(0.016)
Middle	-0.058***	-0.079***	-0.093***	-0.052***	-0.054***
	(0.012)	(0.010)	(0.013)	(0.014)	(0.014)
Log income	-0.030***	-0.020***	-0.030***	-0.033***	-0.038***
	(0.004)	(0.003)	(0.004)	(0.004)	(0.005)
Male salaried emp.	-0.048***	-0.071***	-0.050***	-0.024**	-0.014
	(0.008)	(0.009)	(0.011)	(0.012)	(0.010)
Household head education (Ref. = Illiterate):					
Literate	-0.057***	-0.029	-0.041**	-0.025	0.019
	(0.012)	(0.019)	(0.017)	(0.018)	(0.020)
Primary	-0.097***	-0.067***	-0.047***	-0.038**	-0.066***
	(0.012)	(0.013)	(0.016)	(0.015)	(0.017)
Middle	-0.112***	-0.103***	-0.076***	-0.079***	-0.080***
	(0.014)	(0.011)	(0.014)	(0.016)	(0.015)
Secondary	-0.173***	-0.148***	-0.127***	-0.099***	-0.121***
	(0.014)	(0.012)	(0.015)	(0.017)	(0.017)
Graduate	-0.166***	-0.144***	-0.170***	-0.130***	-0.130***
	(0.022)	(0.018)	(0.022)	(0.026)	(0.025)
Social group(Ref. = Hindu non-SCST):					
SCST	0.085***	0.046***	0.041***	0.063***	0.035***
	(0.011)	(0.011)	(0.015)	(0.017)	(0.012)
Muslim	-0.059***	-0.086***	-0.097***	-0.100***	-0.086***
	(0.010)	(0.011)	(0.016)	(0.014)	(0.013)
Other	0.007	-0.045**	-0.019	0.010	0.012
	(0.018)	(0.017)	(0.027)	(0.028)	(0.029)
Age	0.013***	0.029***	0.023***	0.022***	0.018***
	(0.004)	(0.005)	(0.006)	(0.006)	(0.005)
Age^2	-0.0002***	-0.0004***	-0.0003***	-0.0003***	-0.0003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Children 0-4	-0.022***	-0.017***	-0.022***	-0.034***	-0.036***
	(0.004)	(0.005)	(0.006)	(0.008)	(0.009)
Children 5-14	-0.000	0.001	0.015***	0.002	0.011***
	(0.003)	(0.003)	(0.004)	(0.005)	(0.004)

Table continues on next page.

Table A1.3, continued

Pr(Labor force)	**1987**	**1999**	**2004**	**2009**	**2011**
District male employment shares (Ref. = construction):					
Agriculture	0.295**	0.221**	0.089	0.027	0.276**
	(0.150)	(0.104)	(0.140)	(0.135)	(0.124)
Manufacturing	0.131	-0.031	-0.057	0.207*	0.242**
	(0.136)	(0.099)	(0.124)	(0.119)	(0.096)
Services	0.008	-0.051	-0.086	0.113	-0.010
	(0.141)	(0.091)	(0.121)	(0.103)	(0.091)
White-collar services	0.006	-0.052	-0.191	0.024	-0.048
	(0.143)	(0.114)	(0.148)	(0.139)	(0.126)
District graduate share	0.012	-0.015	0.107	-0.282**	0.078
	(0.127)	(0.093)	(0.119)	(0.125)	(0.106)
N	22176	21143	19648	15807	15307
Pseudo R2	0.175	0.157	0.151	0.138	0.134
FLFP rate	0.174	0.176	0.207	0.179	0.179

Note: Married women age 25-54 with less than secondary education. All estimations include state fixed effects. District-clustered standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.10.

Table A1.4: Estimation results (average marginal effects) high-education subsample

Pr(Labor force)	1987	1999	2004	2009	2011
Own education (Ref. = Secondary):					
Graduate	0.198***	0.204***	0.158***	0.162***	0.166***
	(0.017)	(0.013)	(0.016)	(0.015)	(0.014)
Log income	-0.048***	-0.014***	-0.035***	-0.025***	-0.007
	(0.006)	(0.005)	(0.006)	(0.004)	(0.005)
Male salaried emp.	0.100***	0.049***	0.041***	0.038***	0.013
	(0.015)	(0.014)	(0.013)	(0.012)	(0.018)
Household head education (Ref. = Illiterate):					
Literate	0.026	-0.067**	0.011	0.025	0.041
	(0.076)	(0.033)	(0.065)	(0.043)	(0.048)
Primary	0.058	-0.004	-0.018	0.047	0.049
	(0.064)	(0.043)	(0.050)	(0.037)	(0.037)
Middle	0.026	-0.018	-0.004	0.026	-0.013
	(0.054)	(0.039)	(0.050)	(0.030)	(0.032)
Secondary	0.012	-0.046	-0.037	-0.007	0.001
	(0.050)	(0.032)	(0.043)	(0.026)	(0.027)
Graduate	-0.018	-0.073**	-0.025	0.003	-0.045
	(0.050)	(0.032)	(0.044)	(0.027)	(0.032)
Social group(Ref. = Hindu non-SCST):					
SCST	0.114***	0.077***	0.032	0.052**	0.028
	(0.042)	(0.022)	(0.027)	(0.022)	(0.019)
Muslim	-0.035	0.010	-0.052***	-0.051***	-0.067***
	(0.029)	(0.023)	(0.019)	(0.020)	(0.020)
Other	0.059**	0.054**	0.019	0.028	0.043**
	(0.024)	(0.023)	(0.019)	(0.021)	(0.020)
Age	0.047***	0.020***	0.041***	0.010	0.011
	(0.009)	(0.007)	(0.008)	(0.008)	(0.007)
Age^2	-0.0006***	-0.0002**	-0.0005***	-0.0001	-0.0001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Children 0-4	-0.026***	-0.017**	-0.035***	-0.035***	-0.037**
	(0.008)	(0.008)	(0.011)	(0.011)	(0.015)
Children 5-14	-0.034***	-0.010*	-0.017**	-0.012	-0.002
	(0.007)	(0.005)	(0.007)	(0.008)	(0.007)
District male employment shares (Ref. = construction):					
Agriculture	0.010	0.005	0.268*	-0.093	0.130
	(0.170)	(0.178)	(0.149)	(0.137)	(0.116)
Manufacturing	-0.122	-0.212	-0.001	0.067	0.309***
	(0.148)	(0.133)	(0.144)	(0.107)	(0.098)
Services	-0.194	-0.131	0.129	0.142	0.058
	(0.141)	(0.140)	(0.136)	(0.107)	(0.096)
White-collar services	-0.183	0.055	0.134	0.329**	0.195
	(0.159)	(0.141)	(0.156)	(0.137)	(0.125)
District graduate share	0.022	-0.250**	-0.044	-0.525***	-0.220**
	(0.139)	(0.127)	(0.134)	(0.115)	(0.108)
N	6855	11392	9865	11391	11999
Pseudo R2	0.105	0.118	0.119	0.108	0.085
FLFP rate	0.224	0.184	0.195	0.167	0.178

Note: Married women age 25-54 with at least secondary education. All estimations include state fixed effects. District-clustered standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.10.

Table A1.5: Estimated and reweighted marginal effects of education

	Estimated marginal effects					Reweighted marginal effects			
	1987	**1999**	**2004**	**2009**	**2011**	**1999**	**2004**	**2009**	**2011**
Illiterate	0	0	0	0	0	0	0	0	
Literate	-0.050	-0.063	-0.051	-0.030	-0.026	0	0	0	
Primary	-0.072	-0.074	-0.062	-0.025	-0.027	-0.042	-0.022	0.000	0.000
Middle	-0.067	-0.084	-0.100	-0.060	-0.064	-0.071	-0.065	-0.052	-0.042
Secondary	0.086	-0.020	-0.048	-0.056	-0.041	-0.005	-0.020	-0.051	-0.057
Graduate	0.324	0.217	0.144	0.131	0.151	0.223	0.207	0.183	0.179

Note: Estimated marginal effects from equation (1) in the main text. Reweighting based on the education distribution as reported in table 1 in the main text.

Table A1.6: Age-group-specific marginal effects of education

	1987	**1999**	**2004**	**2009**	**2011**
Age 25-30					
Literate	-0.025*	-0.046**	-0.026	-0.011	-0.081***
	(0.015)	(0.018)	(0.024)	(0.022)	(0.023)
Primary	-0.064***	-0.073***	-0.034	-0.021	-0.015
	(0.012)	(0.015)	(0.026)	(0.017)	(0.027)
Middle	-0.069***	-0.088***	-0.097***	-0.053***	-0.074***
	(0.011)	(0.013)	(0.020)	(0.020)	(0.022)
Secondary	0.051***	-0.044***	-0.045**	-0.057***	-0.041
	(0.016)	(0.014)	(0.021)	(0.018)	(0.030)
Graduate	0.287***	0.166***	0.094***	0.138***	0.103***
	(0.030)	(0.023)	(0.028)	(0.028)	(0.035)
Age 31-36					
Literate	-0.031*	-0.068***	-0.053**	-0.058**	0.045
	(0.018)	(0.020)	(0.024)	(0.029)	(0.036)
Primary	-0.065***	-0.047**	-0.061**	-0.029	-0.017
	(0.017)	(0.018)	(0.024)	(0.030)	(0.031)
Middle	-0.051**	-0.071***	-0.094***	-0.025	-0.048**
	(0.022)	(0.015)	(0.026)	(0.026)	(0.022)
Secondary	0.077***	-0.026	-0.066***	-0.066**	-0.031
	(0.020)	(0.019)	(0.024)	(0.027)	(0.022)
Graduate	0.332***	0.210***	0.166***	0.078**	0.154***
	(0.030)	(0.035)	(0.031)	(0.032)	(0.027)
Age 37-42					
Literate	-0.061***	-0.080***	-0.031	-0.001	-0.033
	(0.019)	(0.027)	(0.028)	(0.028)	(0.031)
Primary	-0.070***	-0.094***	-0.051*	-0.027	-0.054**
	(0.016)	(0.025)	(0.029)	(0.027)	(0.024)
Middle	-0.076***	-0.085***	-0.095***	-0.086***	-0.080***
	(0.019)	(0.024)	(0.030)	(0.024)	(0.025)
Secondary	0.157***	-0.029	-0.028	-0.061***	-0.072***
	(0.025)	(0.025)	(0.027)	(0.022)	(0.024)
Graduate	0.351***	0.247***	0.191***	0.131***	0.166***
	(0.031)	(0.040)	(0.041)	(0.034)	(0.031)

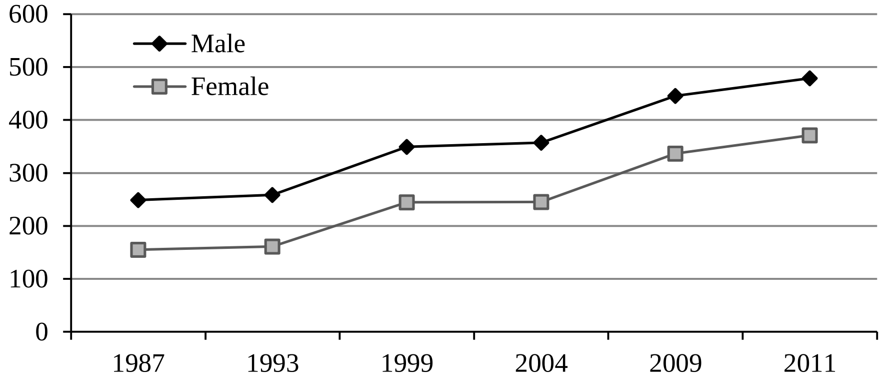
Table continues on next page.

Table A1.6, continued

	1987	1999	2004	2009	2011
Age 43-48					
Literate	-0.091***	-0.058**	-0.058**	-0.091***	-0.009
	(0.019)	(0.023)	(0.024)	(0.027)	(0.028)
Primary	-0.098***	-0.090***	-0.112***	-0.019	-0.020
	(0.022)	(0.020)	(0.025)	(0.029)	(0.024)
Middle	-0.080***	-0.113***	-0.130***	-0.080**	-0.036
	(0.030)	(0.015)	(0.019)	(0.036)	(0.025)
Secondary	0.164***	0.002	-0.052**	-0.046	-0.019
	(0.042)	(0.023)	(0.024)	(0.030)	(0.020)
Graduate	0.432***	0.291***	0.178***	0.183***	0.184***
	(0.045)	(0.035)	(0.039)	(0.037)	(0.041)
Age 49-54					
Literate	-0.114***	-0.068**	-0.146***	-0.011	-0.049*
	(0.021)	(0.027)	(0.035)	(0.044)	(0.027)
Primary	-0.108***	-0.112***	-0.102***	-0.041	-0.051*
	(0.020)	(0.022)	(0.034)	(0.031)	(0.029)
Middle	-0.064**	-0.067**	-0.121***	-0.104***	-0.098***
	(0.029)	(0.026)	(0.032)	(0.023)	(0.026)
Secondary	0.035	0.092***	-0.061	-0.053	-0.058**
	(0.036)	(0.033)	(0.038)	(0.033)	(0.023)
Graduate	0.408***	0.285***	0.124***	0.164***	0.248***
	(0.052)	(0.068)	(0.042)	(0.049)	(0.044)
N	29031	32541	29513	27198	27306

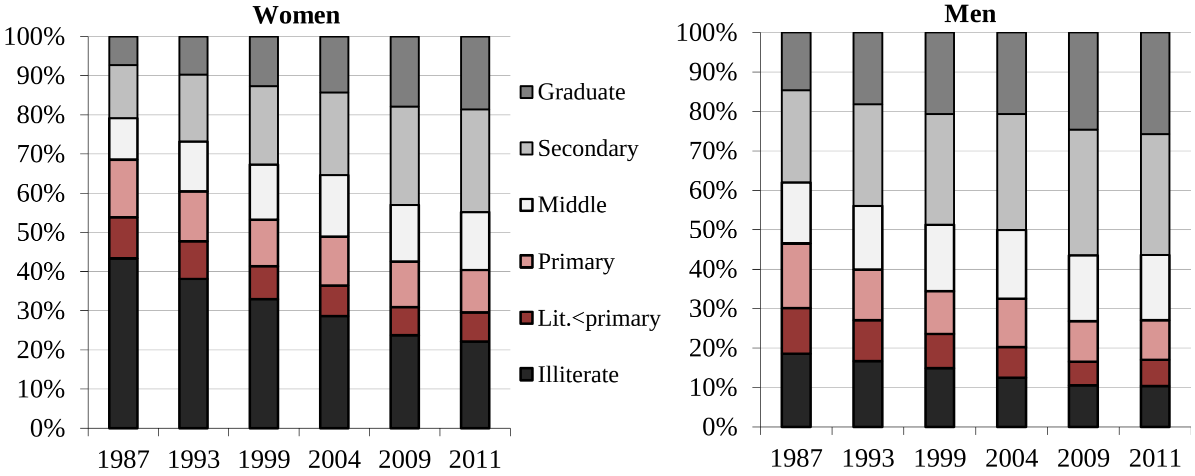
Note: Average marginal effects, calculated after estimation of Equation (1) in the main text, with interactions of age group and education levels. Reference group is illiterate. All variables reported in the main estimation results (table 2 in the main text) are included in the estimation, but not reported here.

Figure A1.1: Real weekly earnings, urban India 1987-2011



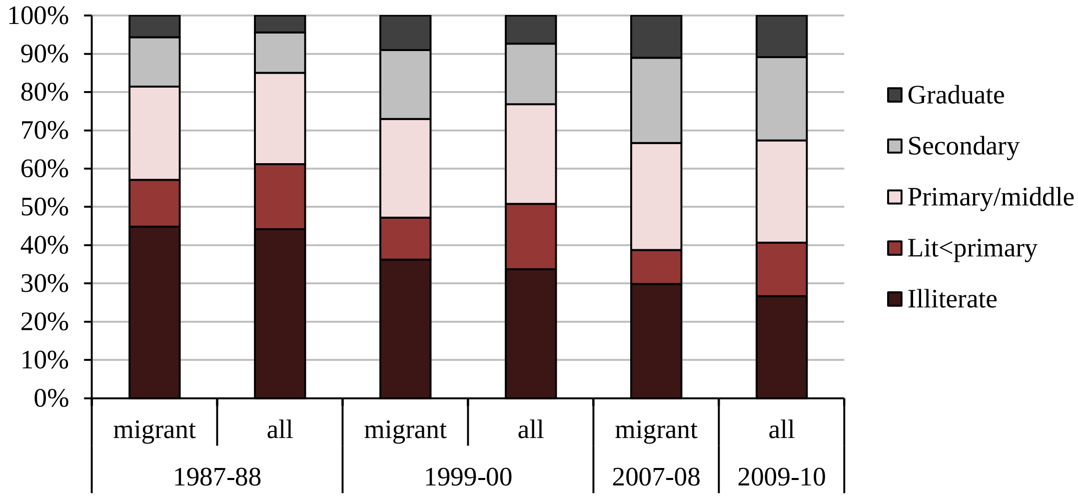
Note: Average total weekly earnings for employees in age group 25-54. Earnings are spatially deflated and in 1987-88 Rupees, based on the Labour Bureau Consumer Price Index for Industrial Workers and Deaton (2003). *Source*: NSS Employment and Unemployment Survey

Figure A1.2: Educational attainment, urban India 1987-2011



Note: Women and men age 25-54. *Source*: NSS Employment and Unemployment Survey

Figure A1.3: Women's educational attainment, by migration background



Note: Women of all ages. *Source*: NSS Employment and Unemployment Surveys for 1987-88, 1999-00, and 2009-10. NSSO (2010) for 2007-08 numbers.

Appendix 2: The effect of wages

To obtain estimates of the own-wage effects on fem.ae labor force participation, we estimate equation (1) in the main text, that is $P_{it} = F(\alpha_{st} + \sum_E \beta_t^E D_{it}^E + \beta_{Xt} X_{it} + \beta_{Zt} Z_{it})$, with the log wage included in X_{it}. Wages are observed only for employed women (regular employees and casual workers) and need to be imputed for all others. As is standard in the literature, this imputation will be based on a wage equation with human capital variables and a number of control variables, as will be explained below. We note, however, that self-employment income and especially the "earnings" of unpaid family workers are unlikely to be predicted well by this equation. The returns to education, for example, are likely to be different for employees versus self-employed workers, but the NSS surveys collect no income or earnings data for self-employed workers so we do not have the data to estimate activity-specific wage equations. In estimating own-wage effects, therefore, we focus on the probability of working for pay in a sample excluding self-employed and unpaid family workers.

We estimate a wage equation with Heckman selection bias correction (Heckman, 1979) separately for each year, regressing real weekly earnings on state, age, age squared, education level, social group, and a variable q_{it} that is further discussed below:

$$\ln w_{it} = \beta_{st} + \beta_{1t} X_{it}^W + \beta_{2t} q_{it} + \beta_{3t} \lambda_{it} + u_{it}\,, \qquad \text{(W1)}$$

where the vector X_{it}^W contains the variables listed above, and λ_{it} is the sample selection correction term. The latter is obtained (as the inverse Mills ratio) from a probit model for labor force participation. This selection equation is equal to equation (1) in the main text, except for the expected market wage that is replaced by q_{it}:

$$P_{it} = F(\alpha_{st} + \textstyle\sum_E \beta_t^E D_{it}^E + \beta_{Xt} X_{it} + \beta_{Zt} Z_{it} + q_{it}). \qquad \text{(W2)}$$

The selection effect in equation (W1) is identified by the district variables vector Z_{it} and the variables in X_{it} that are not included in X_{it}^W, namely income, security of income, underemployment of household members, education of the household head, the number of children by age group, and the presence of in-law parents.

For all women in the sample, the predicted log wage $\ln \hat{w}_{it}$ used in the estimation of equation (1) is the linear prediction based on equation (W1) (excluding the sample selection term). The own wage effect is thus identified through the variable q_{it}. As Heim (2007) discusses, past studies have used a variety of methods to identify the own wage effect on female labor supply, but there is usually no truly exogenous source of variation in wages that can be used. Policy changes such as tax reforms have been used for difference-in-difference estimations, but even if such reforms have taken place they do not allow for a comparison of own wage effects over time for a sample of women representative of the female working age population.

For lack of truly exogenous variation in wages, we compare own-wage effects identified from two different sources of variation.[28] First, we use interactions of state, education level, and age group dummies (age 25-29, 30-39, 40-49, and 50-54) to identify the own wage effect. This is related to grouped estimations of women's hours worked in Blau and Kahn (2007), which is equivalent to using group membership dummies as instrument for the wage in a linear labor supply model (Angrist, 1991). Second, we use spatial variation in wages, taking for q_{it} the average wage of other women in the same district. Reflecting the local labor market, the district average wage should be a good predictor of women's own wage. We also estimate the model without the own wage to check the robustness of other coefficients.

Results are summarized in Tables A2.1 and A2.2 below, which report the marginal effects of the own-wage, education, and household income. Estimates for other variables are not shown but are almost identical across the three specifications. Results for the specification excluding the own wage (table A2.1) are furthermore very similar to the results in the main text, despite dropping self-employed women from the sample. In columns 1-4 of Table A2.2, the own wage effect is identified by state-education-age group dummies. We find a positive own wage effect for all years, though the effect is economically small. A wage difference between state-education-age groups of 10 percent (i.e. a difference of 0.1 in the log wage) corresponds to a difference of around 0.25 percentage points in labor force participation. In columns 5-8, where the own wage effect is identified on variation across district, we see a negative own wage effect (though not significant at the 5% level except for 1987), showing that FLFP tends to be lower in high-wage districts.

As discussed above, in both specifications the exclusion restrictions are not necessarily satisfied, resulting in potentially biased estimates. For example, if district average wages capture general living standards beyond what we are able to control for with total household earnings and household head education, the estimates are biased downwards due to negative income effects. The group dummies, on the other hand, are more likely be correlated with human capital characteristics that are positively linked to labor force participation, as they capture variation across cohorts from the same state and with the same educational attainment. This could for example include the quality of education. Because the estimates are different in

[28] Two recent studies on female labor supply in the US (Blau and Kahn, 2007; Heim, 2007) find own wage estimates and changes in estimates comparable across several specifications. Even though, arguably, none of those estimates is properly identified, the robustness across specifications gives credence to their findings.

sign, we believe it is best not to draw any conclusion regarding the importance of wages for women's labor for participation in urban India. Most importantly, the estimated effects of education show very similar patterns across education levels and over time whether or not we control for wages.

Table A2.1: Marginal effect on the probability of wage employment

Pr(emp)	**1987**	**1999**	**2004**	**2009**	**2011**
Own education (Ref. = Illiterate):					
Literate	-0.036***	-0.050***	-0.029**	-0.038***	-0.012
	(0.007)	(0.010)	(0.012)	(0.010)	(0.011)
Primary	-0.056***	-0.056***	-0.048***	-0.028***	-0.022*
	(0.006)	(0.009)	(0.011)	(0.009)	(0.013)
Middle	-0.046***	-0.068***	-0.072***	-0.053***	-0.055***
	(0.008)	(0.009)	(0.010)	(0.009)	(0.010)
Secondary	0.108***	0.016	-0.005	-0.035***	-0.033***
	(0.012)	(0.011)	(0.014)	(0.010)	(0.011)
Graduate	0.343***	0.235***	0.187***	0.160***	0.177***
	(0.019)	(0.019)	(0.022)	(0.020)	(0.020)
Log income	-0.036***	-0.018***	-0.035***	-0.030***	-0.022***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
N	27122	30323	26953	25527	25573
Pseudo R^2	0.19	0.16	0.17	0.17	0.14

Note: Sample includes married women age 25-54 who are not self-employed or head of their household. Further control variables are listed in the main text. District-clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table A2.2: Estimated average marginal effects with own wage

	State-education-age group					District average wage				
Pr(emp)	**1987**	**1999**	**2004**	**2009**	**2011**	**1987**	**1999**	**2004**	**2009**	**2011**
Log wage	0.003	0.027***	0.028**	0.021***	0.031***	-0.096***	-0.146*	-0.084	-0.031	-0.036
	(0.008)	(0.008)	(0.013)	(0.006)	(0.008)	(0.033)	(0.080)	(0.056)	(0.039)	(0.047)
Own education (Ref. = Illiterate):										
Literate	-0.031***	-0.045***	-0.052***	-0.034***	-0.027***	-0.022***	-0.029***	-0.030***	-0.029***	-0.019**
	(0.009)	(0.009)	(0.013)	(0.012)	(0.010)	(0.005)	(0.006)	(0.009)	(0.007)	(0.008)
Primary	-0.054***	-0.061***	-0.072***	-0.032***	-0.039***	-0.037***	-0.049***	-0.049***	-0.027***	-0.034***
	(0.006)	(0.009)	(0.009)	(0.010)	(0.009)	(0.004)	(0.004)	(0.010)	(0.008)	(0.008)
Middle	-0.047***	-0.068***	-0.086***	-0.061***	-0.067***	-0.007	-0.051***	-0.058***	-0.049***	-0.054***
	(0.008)	(0.009)	(0.011)	(0.009)	(0.009)	(0.014)	(0.004)	(0.011)	(0.010)	(0.009)
Secondary	0.083***	-0.017	-0.040*	-0.049***	-0.051***	0.302***	0.251*	0.126	-0.008	0.004
	(0.021)	(0.015)	(0.021)	(0.011)	(0.009)	(0.078)	(0.147)	(0.090)	(0.031)	(0.037)
Graduate	0.309***	0.148***	0.115***	0.116***	0.099***	0.627***	0.649***	0.435***	0.278**	0.296**
	(0.041)	(0.031)	(0.040)	(0.025)	(0.020)	(0.076)	(0.129)	(0.146)	(0.126)	(0.138)
Log income	-0.032***	-0.019***	-0.033***	-0.025***	-0.021***	-0.032***	-0.019***	-0.033***	-0.026***	-0.022***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
N	27123	30323	26953	25527	25573	26686	29801	26593	24945	24883
Pseudo R^2	0.19	0.16	0.17	0.17	0.14	0.19	0.16	0.17	0.16	0.14

Note: Sample includes married women age 25-54 who are not self-employed. Further control variables are listed in the main text. Bootstrapped standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.10.