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Working Paper

Motherhood and labor market penalty: a study on Indian labor market

GLO Discussion Paper, No. 673

Provided in Cooperation with:
Global Labor Organization (GLO)

Motherhood and labor market penalty: a study on Indian labor market

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Abstract:

Labor market penalty associated with motherhood (in short, motherhood penalty) is an important issue related to gender equality in the society. Our paper is an attempt to empirically examine the extent of motherhood penalty in the context of Indian labor market. We use a nationally representative longitudinal survey data to address this question. We find negative relationship between motherhood and labor market outcomes for women. Besides using conventional measures of motherhood such as number of children, we also devise a new measure of motherhood relevant for our research question. The survey asked the respondents about their desired number of children. We deduct the desired number of children from the actual number of children to come up with a new measure of motherhood that we call extra children. We reckon that often women's decision to join specific occupations or labor markets in general often internalize their desired number of children; the number they originally planned for. Hence, it is the number of children above the desired number which leads to stronger negative outcomes in the labor market. We find that the extra children variable has a stronger negative impact on women's labor market outcomes than the conventional measures. We also examine how the extent of motherhood penalty varies across different cultural values pertaining to different family settings, regions and workplaces. We find, depending on different cultures prevailing in the places of residence or workplace, motherhood penalty gets either mitigated or exacerbated. Our results remain robust to alternative measures of motherhood.

JEL Classification: J16, J31, O15

Keywords: India; Gender equality; Motherhood; Labor market penalty

1. Introduction

Labor market penalty associated with motherhood (or in short, motherhood-penalty) that has been documented in different countries across the globe, has some serious implications for fertility choice and intra-household resource allocation. This issue is particularly important for India which, despite its impressive performance in terms of GDP growth rate since Indian economy was liberalized in 1991, showcase one of the lowest women labor force participation rates in South Asia and motherhood may have an important role to play in women's labor market outcomes. There are several newspaper reports and anecdotes how women, unable to find the balance between child rearing and their professional lives, decide to quit labor force in India and yet, there is a surprising silence in academic research, barring a few, sporadic attempts, regarding quantitively estimating motherhood-penalty for Indian labor market. In our work we fill this gap first by estimating motherhood penalty using a nationally representative longitudinal survey data and then see how family, work and social culture mitigate (or exacerbate) the extent of motherhood penalty.

The existing research shows, which we will detail shortly, that motherhood-penalty exists in developing and developed countries alike. But why are mothers penalized in the labor market? The answer is largely based on what is loosely referred to as "specialization hypothesis" sees household as a production unit jointly run by the husband and wife. After a child is born in the family, the demand for household work increases greatly and in response to that, according to the specialization hypothesis, women specialize more in household work and men in outside work and thereby causing motherhood penalty and fatherhood bonus. The specialization pattern where women specialize in child rearing and men in working in labor market emanates either from the comparative advantage women have in raising the child for biological reasons (Becker, 2009) or from asymmetric gender norms and power relations prevailing in the society (Berk, 2012). In response to the demand for specialization, women may either quit labor force or may opt for shorter work hours or part time jobs (Weeden et al., 2016). It is also possible that in apprehension of lower work effort from mothers (who are presumably burdened with their child rearing responsibilities) employers actively discriminate against mothers(Budig, 2001; Correll et al., 2007).

The simplest way to find motherhood-penalty can be done by estimating the *direct effect* of having a child on a mother's wage *ceteris peribus*. The direct effect is captured by the coefficient of the presence of children in the log earning equation controlling for human capital variables. But loss in immediate wage may not be the only form of motherhood-penalty as motherhood creates dynamic impacts on a woman's labor market outcomes which unfold over time. The research papers in labor economics have shown that after having a child, many women exit the work force. While some of them re-join the workforce after a gap, others become full-time mother. Even those who can manage to return to work force, suffer from productivity and efficiency loss along with loss in work experience which have long term consequence on their professional growth. Women with children often internalize this by opting for jobs with low pay but flexible work hours. Anderson et al.,(2013) estimated a total motherhood wage gap of 15 prcent using National Longitudinal Survey of Labor Market Experience of Young Women (NLSYW). They also argue that intermittent absence from the labor market are likely to reduce wages because general and firm specific skills depreciate and workers lose rents associated with good job matches. It is however possible that the low-skilled workers may be less vulnerable to such earnings erosion, since they have less human capital and their wages consist of less of economic rent. Thus, the opportunity cost of motherhood for low skill, low paid female labor is comparatively lower than that for the high skill high paid female workers as for the former group the chance of skill loss or atrophy is nominal. In another estimates of motherhood penalty, Budig & England, (2001), found a seven percent wage gap between mother and non-mother which comes down to 5% per child for mothers with more than one child when authors put control for experience. In their paper, based on National Longitudinal Survey of Youth, 1982-1993, they also found a modest wage premium for married women.

Motherhood-penalty – characterized by wage foregone by a mother for taking care of her children – depends crucially on the socially prevailing images of ideal worker and ideal mother(Jacobs & Gerson, 2004). While the first one comes from her workplace culture, the other one emanates from the cultural norms prevailing in her household. This image of an ideal worker working long hours in office comes in direct conflict with the image of ideal mother and more often than not, mothers respond by going out of the work force or opting for work with flexible shifts but limited opportunity of advancement; jobs that are commonly referred to as *the mommy track* (Mason & Ekman, 2007). It has been found that 25% of white, college educated, married women with children in the United States quit their jobs to become full time mother (pg 9, Stone, 2008). Even though the women's choice to give up their career prospects is lauded in media, this is hardly her personal choice as a host of social norms pertaining to family and workplace play important roles behind them (Blair-Loy, 2009; Stone, 2008).

The wage gap between mothers and non-mothers however, widens with time and such divergence largely comes from non-linearity in the relation between wage rate and work hours – long work hours are rewarded disproportionately (Goldin, 2014; Weeden, 2016). Long work hours are more typical in occupations where complexity of the job makes it difficult to verify work (and shirking) and write a contract. In occupations such as law, medicine, management and information technology work, long work hours often become an instrument used to signal one's worth in the firm. The signal of long work hours is used so frequently in these occupations that often it becomes an internalized norm – it becomes an integral part of an ideal worker's image. The women who take a temporary break from work also suffer from loss in wages. One estimate shows that women's annual earning fall by 30% when they stay out of the labor market for 2-3 years(Rose & Hartmann, 2004).Such choices are often made by women with very high human capital who typically have degrees in law, medicine or management who typically work in high-end professions.

Organizational culture, among other factors, contributes significantly to rising work hours which in turn make motherhood less compatible with work force participation. It is been generally observed that in the recent past there has been an emergence of organizational culture which demands full time devotion from the workers. Such culture puts the women in general (and mothers in particular) in disadvantage as the social norm wants them to take care of the household chores. Faced with this contradiction, women often opt out of long working hours. American residents surveyed in Current Population Survey in 2000 reveal that 37% of men working in managerial, technical and professional jobs work for more than 50 hours in a week, while this figure is only 17.1 percent for women. This pattern is completely opposite for work comprising less than 30 hours in the same occupation category. There we have 5.8% of men compared to 14.8% of women (pg-33, Jacobs & Gerson, 2004).

Fatherhood bonus – a mirror image of motherhood-penalty which can also be explained by the *specialization hypothesis* – is also well documented in the literature. In one of the earlier studies, Lundberg& Rose(2002) found evidence of fatherhood premium in the United States labor market. They found that father's wage and labour supply were significantly higher than non-father males. More interestingly, they found that men's labor supply and wage rates increase more in response to the birth of sons that to the births of daughters. Whitehouse(2002)found evidence of motherhood penalty and fatherhood premium in the context of labor markets of United Kingdom (UK) and Australia. She concluded that in UK, motherhood penalty and fatherhood premium can partly be explained by the pattern of wage distribution and wage structure of part time jobs. Studies establishing the existence of motherhood penalty in the United States labor market, also confirmed the presence of its mirror image – fatherhood bonus (Amuedo-Dorantes & Kimmel, 2005; Anderson et al., 2003; Budig & Hodges, 2010; Glauber, 2008; Gough & Noonan, 2013; Weeden, 2016)

The discussion above showcase a substantial body of research that we discussed above is based on data and case studies from the United States and Europe. We could not find many papers that look at the issue of motherhood penalty in India. In one of the earliest studies that did not directly focus on motherhood penalty, Desai & Jain(1994), looked at the relationship between maternal employment and child care activity in South Indian rural families and found that such relationship crucially depends on the social context of the work. In many poor families in rural South India, women do not have time to solely look after her children. In such a set-up, the authors concluded that time allocation between child care, domestic work and wage-earning work need to be analysed as jointly made decisions which often result from lack of work opportunity for women. While Desai and Jain focused on rural India, Rajesh (2013) looked at the impediments of the women who quit their corporate jobs at the time of child birth and trying to enter the labor market after taking a break. A more comprehensive study using nationally representative data has been attempted by Das & Žumbytė, (2017) who using National Sample Survey (NSS) rounds from 1983 to 2011 showed that with professional child care virtually non-existent in India, children's age plays a crucial role in a woman's decision to work; women with young children are less likely to join the work force. Moreover, they find that women's probability of employment increases if they live with older children and other women with more than 50 years of age who can presumably take care of the children at home. Besides these studies, there is one more study looking at the issue using experimental methodology. Bedi, Majilla, & Rieger (2018), in an attempt to estimate employer's bias against mothers, sent out fictitious CVs to employers. Besides parenthood status, they indicated whether the applicant is coming from matrilineal or patrilineal culture. They found that *mothers* from patrilineal societies are less likely to get call back than men and women without children. Mothers from matrilineal background face no such discrimination.

In our paper, we estimate motherhood penalty in the Indian labor market using a nationally representative data set. Most importantly this data set allows us to use panel data techniques that takes care of unobserved heterogeneity. In particular, we using longitudinal data collected in two rounds – 2004-05 and 2011-12, we see if number of children did have any effect on women's wage and working hours. The results confirm the existence of motherhood penalty. However, its magnitude varies with occupation the woman is in, her family composition and the number of children.

2. Data

We use the 2004-05 and 2011-12 waves of India Human Development Survey Data (IHDS) data. IHDS database was initially formed through a survey of 41554 households in 1503 villages and 971 urban areas spanning across 35 Indian states and union territories conducted by Indian Council of Applied Economic Research (NCAER), New Delhi and University of Maryland in 2004-05. The survey consists of two parts, household questionnaire with household characteristics on demography, health, education, income, work, occupation, production, consumption, assets, social capital, fertility, children schooling, etc. and individual questionnaire with work, income, gender relation, fertility decision, marriage practices, exposure to mass media, reading, writing skill etc. The respondent households of 2005 survey were re-interviewed in 2011-12 to form a longitudinal database. The number of households increased slightly in the second round and it interviewed 42152 households. We however, do not use the full sample. We rather use the sample consisting of *eligible women* – married women in the age group 15-49. Even though it could have been ideal to compare mothers and non-mothers, around 90% of our eligible women were mothers when the first round of the interviews was conducted in 2005. We therefore, look at how the number of children born between 2005 and 2010 on the wage and work participation of these eligible women.

3. Empirical Strategy

3.1 Empirical Model

In our paper, we test whether, controlling for other factors, a woman's earning and work participation changes with change in her motherhood status measured by different possible metric we discuss below. Besides wage difference, we also examine the impact of motherhood on work hours as it is often reported in the literature that after becoming mothers, many women drop out of the labor force or move to part time jobs in order to accommodate their child rearing duties. The most critical methodological challenge in this literature is to deal with the selection bias – in a cross section setting women who have decided to become mothers and who did not, are likely to come from different socio-economic strata which may leave direct impact on their employment status and wage. We deal with this problem by taking an individual level fixed effect model. In particular, we start our estimate the following model

$$y_{it} = \beta_0 + \mu_i + \beta_1 m_{it} + \beta_1 X_{it} + \epsilon_{it}$$

Where y_{it} represents the outcome variable, which can be wage or employment status, for individual *i* and period t. In our baseline specification, m_{it} represents some measure of motherhood for the woman *i* in period t. However, it is of critical importance how we measure motherhood which we discuss now.

3.2 Measuring motherhood

There are various possible ways to measure motherhood. The most obvious one is the status of motherhood which classifies women in mother/non-mother binary and many researchers have used that measure. The problem of using that measure in our study is two-fold. The first one is generic; a mother of five children is different from a mother of one child and that heterogeneity is lost if we use the binary measure. The second problem is specific to our data set. In our data, we use individual level fixed effect model that essentially compares relationship between an individual's motherhood and labor market outcomes between two time periods. But in our data around 90% of the respondents were mothers in both the periods. Hence, by using the binary measure of motherhood we are not left with much variation in motherhood status to exploit. Nevertheless, we use that measure in our robustness section.

The measure of motherhood that we use in our baseline regression is the numbers of children conceived by a woman and estimate its effect on her labour market outcomes. We use this measure in our initial baseline regressions. However, the survey asks the women about the number of desired children. We use this variable to construct a new variable called *extra children* which is calculated as difference between actual and desired number of children. We reckon that the effect of the desired number of children can be internalized in the women's labor market outcomes and it is the extra children which impose the burden of penalty. We use *extra children* as our principal measure of motherhood for the rest of the regressions.

4. Results

4.1 Descriptive Statistics

In this paper, we look at the effect of number of children on labour market outcomes such as work participation and wage. We have already discussed above that we expect more children to be associated with lower work participation and wage for the women. Before we formally test our hypotheses, let us have a look at the summary statistics of different dependent and independent variables.

We start by looking at the motherhood status of women. It is important to note that our working sample consists of ever married women between 15 and 49 otherwise called as eligible women in IHDS documentation. In the next table we present the descriptive statistics for both our main independent variables involving motherhood status and main dependent variables involving employment related information.

Table 1: Descriptive statistics

In the table above, we present descriptive statistics for relevant variables which include both explanatory and outcome variables for our regression analysis. In panel A of the table we present summary statistics for variables capturing motherhood. We present summary of all the variables for IHDS rounds 1 and 2 conducted in 2005 and 2012 respectively. In the first row of panel A, we find that 93% of the eligible women had at least one child at the time of round 1 which further increased to 97% at the time of round 2. However, total number of respondents also decreased between the survey rounds due to attrition as some women who are aged between 39-49 in 2005 have crossed the age limit of 49 in 2010 and therefore are not included in the second round of the survey. The average number of children was 2.68 in 2005 (time of round 1) which increased slightly to 2.89 in 2010 (time of round 2). In the previous section we talked about the definition of the newly created variable extra children. In 2005, the average number of the extra children is below 1 (.258) but its standard deviation is 1.424 indicating wide variation of response across the respondents. The mean of this variable however, got almost doubled to reach 0.42 in 2010 but the standard deviation decreased slightly to 1.26.

Panel B of table 1 show different work-related variables which we use as the outcome variables in our regression analysis. We see that yearly work hours on an average declined from 1239 hours to 1183 hours. Average hourly wage, on the other hand increased from approximately Rs. 13 to Rs. 18. The fraction of eligible women who are employed increased between these two rounds as well, but it was largely driven by increase in part time employment even though full-time employment increased marginally as well.

Panel C of the table represents the summary statistics for the other control. We find that the average age of the sample was around 33 in the first round which increased to 38 in the second. Between the two survey rounds, the average household size declined from 6.2 to 5.6 while average years of education largely remained stable around 4 years – 4.2 in IHDS 1 and 4.5 in IHDS 2.

Besides the variables summarized in table 1, there are two more variables that we need to explore and they are best understood in terms of their distribution. In our regression analysis, we deploy individual level fixed effect regression and therefore, through these regressions, we will be examining the effect of the number of children conceived by a woman between the survey periods, on her labor market outcomes. Therefore, it is important to look at the distribution of the number of children born between 2005 and 2010. The information is directly provided through the survey and we summarize the information in the following graph:

Figure 1: Distribution of children conceived between since Jan, 2005 (From IHDS 2)

We find that most of the women (around 70%) did not give birth to any children between two survey rounds, followed by 1 child (around 17%), 2 (around 10%) and 3 (around 2%) children.

Besides this distribution, another one is worth exploring in the context of our problem. We examine the fraction of eligible women employed in different occupations. We use three broad categories of occupations – farming jobs, blue-collar and white-collar and present the distribution in the following figure.

Figure 2: Distribution of eligible women across different occupational groups (IHDS 1 and 2).

From the graph it becomes clear that there is a considerable variation of relative importance of different sectors across survey rounds. In round 1, farming jobs accommodated most of the eligible women, followed by blue-collar and white-collar jobs. In round 2, there is a change in importance across the sectors as blue-collar jobs becomes the biggest category. However, the category of white-collar job remains the third highest category in both the rounds.

4.2 Baseline Regressions

In our baseline regressions, we start by examining the effect of number of children on work participation and number of jobs. In motherhood-penalty estimation, like many other reduced form estimation exercises, the biggest challenge is to deal with the endogeneity issue. We address this problem by exploiting the panel structure of the data and using individual fixed effect. In a fixed effect model, we are essentially comparing an individual in 2005 with herself in 2012 in terms of fertility and labor market outcomes. In this process, all the time invariant, individual (and her household) specific unobservable variables get controlled in the regression. In the next table, we show the regression results with the number of children as our main independent variable of interest and use log wage, log work hours, whether employed, whether employed as part-time or full-time as our outcome variables.

Table 2: Baseline regression with number of children as measure of motherhood

As control variables, we add age of the respondent woman as both labor market outcomes and fertility change with the age. We also expect some nonlinear relationship between age and labor market outcomes and in order to test that we add the age squared term in the regression. We also add variable capturing one's level of education. We have divided the respondents in five educational categories – illiterate (category 0), primary (category 1), secondary (category 2), higher secondary (category 3) and undergraduate and above (category 4). We take category 0 as the reference category. For the first two outcome variables we also add occupational categories as these two regressions only involve employed women. We use three broad categories – farm jobs (category 0), blue-collar jobs (category 1) and white-collar jobs (category 2). For three outcome variables capturing employment status for which regression coefficients are reported in column (3)-(6), we skip the occupational categories because these regressions also involve unemployed women who do not have any corresponding occupational categories. Besides these, we also add family level controls such as household size and asset position. Rather than controlling for the actual value of the asset, we control for their relative asset positions by controlling for the asset quintile they belong to.

We find that the number of children is negative and significant for wage and employed status of eligible women. This indicates that with a greater number of children, women either quit their jobs or stay in the job but earn less hourly wage. For work hours, full time and part time employment, the coefficient is negative but not significant. Among the control variables, age is consistently positive and significant across all regressions. So is age squared – negative and significant. Household size is negatively related with all the outcome variables but it is only significant for employment status variables.

The result we got here is not showing as strong penalty as we have presumed. One possible reason could be that motherhood is often planned and it is possible for a woman to internalize the cost of motherhood by adjusting other variables. So, now we run the regressions with the extra children, which we defined earlier, as the main measure of motherhood. In the next table, we regress the same set of outcome variables on this "extra children" which is calculated by deducting desired number of children from the actual number of children.

Table 3: Baseline regression with number of extra children as measure of motherhood

We find that extra children variable has a stronger connection with the labor market outcomes. The coefficient of extra children is negative and significant for all outcome variables except full time employment for which the coefficient is negative but not significant. This indicates that women with extra children work less and earn less. The pattern remains same for employed status and women in part time jobs. Control variables such as age, and household continue to affect the outcome variables in the same manner as it did in the last regression. Additionally, it seems that women are less likely to work at a higher asset level.

4.3 Heterogeneity Analysis

Motherhood-penalty, as we have discussed in the introduction, results from the conflict between the image of ideal worker and that of ideal mother prevailing in a society and the way the society attaches social prestige with motherhood status. This essentially means that the degree of motherhood penalty depends on social norms which at macro level varies across societies and at a micro level varies with workplace and family environments. In the analysis that follows, we will examine how the degree of motherhood penalty varies across different social, family and workplace environments.

4.3.1 Heterogeneity in social environment

Geographical location

In the previous section we have established the existence of motherhood penalty irrespective of differences in age, education, occupation, family structure and asset positions. But India is a vast country encompassing different cultural values and social organizations. In this section we will try to explore how motherhood interacts with the parameters pertaining to different social environments. More specifically, we exploit the regional variation within India to ask if the social structures prevailing in different parts of India can mitigate the labor market penalty imposed on the mothers. In this exercise we divide India using different cleavages with the same principle – one side of the cleavage is believed to be more patriarchal than the other. We start by North India-South India division as many researchers have pointed out the existence of more patriarchal culture in North India which can be attributed to the agricultural technology that used in the North traditionally (Alesina et al., 2013).

In our regression we interact the variable named extra children with the Southern state dummy which takes 1 if the state of residence of the respondent is a Southern state, 0 otherwise. The list of Southern states comes from Ministry of Statistics and Program Implementation (MOSPI) website and includes Daman and Diu, Dadra & Nagar Haaveli, Maharashtra, Andhra Pradesh (this is old Andhra Pradesh and therefore includes present day Telengana), Karnataka, Goa, Kerala, Tamilnadu and Pondicherry. The result is reported below:

Table 4: Heterogeneity analysis: Southern states vs rest of India

We find that the level effects of extra children remain negative significant for all the labor market outcomes meaning that compared to Southern states the motherhood penalty is higher in rest of India. But barring part time employment, for all other outcome variables the interaction effect of extra-children and Southern state dummy is positive significant implying that that at least part of the motherhood penalty is mitigated in the Southern states which have more equitable gender norms.

Rural Urban

In this subsection, we look at the heterogeneity analysis between rural and urban areas. Our a-priori belief is that gender norms are more equitable in urban areas and women's work opportunities are better. Therefore, we expect that motherhood penalty, at least partially will be mitigated in urban areas. In the regression, we interact the extra children variable with the urban dummy and report the results along with other controls.

Table 5: Heterogeneity analysis: Rural vs Urban

We find that the level effect of extra-children is still negative significant for almost all outcome variables. But the interaction terms are not significant meaning that there is no significant difference between rural and urban areas in terms of motherhood penalty.

Classification based on women's labor force participation rate: High and Low

The North-South or Rural-Urban classification is rather ad-hoc and based on the general notion about differential gender norms prevailing in either side of these cleavages. Next, we look at the classification based on variables which captures the level of gender inequality in a state. First, we use the rate of women's labor force participation rate (WLFPR) as the dividing principle— based on Indian census 2001, in the states where the rate is more than the national average, we call them High WLFPR states and the rest are called the low WLFPR states. The states falling in the Low category are Jammu and Kashmir, Punjab, Chandigarh, Haryana, Delhi, Uttar Pradesh, Bihar, Assam, West Bengal, Odhisa, Gujarat, Daman and Diu, Dadra and Nagar Haveli, Goa, Kerala and Pondichery. The rest of the states and union territories are High WLFPR states. Similar to the previous regressions, we create a High WLFPR state dummy and interact with the extra-children variable and focus on it as our main independent variable of interest. The results are reported below:

Table 6: Heterogeneity analysis: High vs Low WLFPR states

The level effects of extra-children continue to be negative. The interaction effect gives mixed results effect except for full time employment where interaction effect has a strong positive significant effect thereby mitigating the motherhood penalty to some extent in High WLFPR states. In particular, the interaction effect is positive and significant for full-time jobs. This is consistent with our expectation as in high WLFPR states the general culture of employing women must be better than that in low-WLFPR states. For wage however, there is no significant difference between the High-WLFPR and Low-WLFPR states

Classification based on sex-ratio: High and Low

In this subsection, we classify states based on sex-ratio --another indicator of state level gender norm. We call a state High sex-ratio state if its sex ratio is higher than the national sex ratio which indicates a gender norm more equitable than the national level. Our classification is based on Indian census, 2001 figures and the High sex-ratio states are Kerala, Puduchery, Tamil Nadu, Andhra Pradesh, Chattishgarh, Meghalaya, Manipur, Orissa, Mizoram, Goa, Karnataka, Himachal Pradesh, Uttarakhand, Tripura, Assam, West Bengal, Jharkhand and Lakshadweep. We create a High SR dummy and interact with the extra children variable.

Table 7: Heterogeneity analysis: High vs Low sex-ratio states

We find that the level effect of extra children is by and large negative. The interaction effect is negative significant for wage. But for all other outcome variables – work hours and employment status—they are positive and barring the coefficient on part-time employment, they are significant as well.

4.3.2 Heterogeneity in family environments

In the last section, we looked at the motherhood penalty in presence of different social environments. In this section, we look at the effect of motherhood penalty in presence of different family environment. Specifically, we examine whether motherhood penalty gets mitigated if the family is rich and if women in the family has higher female autonomy.

Family Wealth

In this section, we examine the difference in motherhood penalty across families with differential wealth levels. In order to examine this, we create an interaction variable by multiplying the wealth quintile the family belongs to with the extra-children variable.

Table 8: Heterogeneity analysis: Family wealth-based classification

We find that among different specifications, the sign of the coefficient of the interaction variable is positive for wage and work hours but not significant, while the level for these variables are negative and significant. For the employment status outcome variables, neither the level effect of the extra-children nor the interaction variables are significant. Asset levels are generally negatively related with labor market outcomes suggesting that as families get richer, women are more likely withdraw from the labor force.

Female autonomy

Next, we examine how the extent of motherhood-penalty varies across families with female autonomy. One would expect that with more female autonomy, the extent of motherhood penalty would be less. In this case, we select a particular question to quantify the extent of female autonomy and it pertains to a particular area – fertility decision. The question asks who has the most say regarding the number of children. There are 5 possible answer to this question – the respondent, her husband, senior male of the household, senior female of the household and others. We divide these responses in two groups --- whether the woman has *most say* or anyone from the other four categories. We use this binary variable to divide families in two groups. In families where the woman has the most-say, we consider them as families with female autonomy and we reckon that in such a family, the woman, while taking fertility decision will internalize the labor market penalty she is going to bear.

For constructing the interaction variable, we create a dummy variable which takes the value 1 if others take the decision and 0 if the woman takes the decision. We then create the interaction variable by multiplying the binary variable with the number of extra children.

Table 9: Heterogeneity analysis: classification based on female autonomy in the family

We expect that the motherhood penalty will be enhanced in families where other take the fertility decision for the woman which means that the sign of the coefficient for the interaction variable will be negative. Our expectation is confirmed for two outcome variables – employed and employed part-time. For these two outcomes, the level effects of other people taking decision are also negative and significant. This means that at least in terms of these two variables, motherhood penalty is exacerbated for women whose fertility decision is taken by others. For other outcomes, the interaction is not significant.

4.4 Robustness check

Dummy for number of children

In this section, we do robustness checks by taking alternative measures of motherhood for estimating the labor market penalty. First, we create a dummy for the number of children – 1,2,3,4 and 5 or more. The reference category is no children. Using this, we would like to see if there is a number of children after which the penalty sets in. The results are reported below.

We find that for wage, the penalty is associated with 3 children and 5 or more children. For work hours, the effect is negative and significant for 4 children. For all other categories, the coefficient is negative but not significant. For employment status variables however, the coefficients for all categories are however, negative and significant.

Table 10: Robustness check: dummy for the number of children

Dummy for mothers

In this section, we use a motherhood dummy which takes the value 1 if the woman has any child and 0 otherwise. We have already discussed the problem of using this measure; there is not much variation in this variable between two rounds as even in 2005, most of the respondents had at least one child. It may create a problem for fixed effect estimation, which essentially estimates the effect of variation between two time periods.

Table 11: Robustness check: dummy for motherhood.

We find that the coefficients of the motherhood dummy are negative but not significant for wage and work hours. However, it is throughout negative and significant for all the employment status variables which suggest that women, upon becoming mother drop from the workforce.

5. Conclusion

In this paper we estimated the extent of the labor market penalty associated with motherhood in the context of Indian labor market. To the best of our knowledge, among a handful of studies which studies motherhood penalty in the Indian context, ours is the only one which uses the panel data structure. In our analysis, we have shown that different measures of motherhood are negatively associated with women's labor market outcomes. We have also shown that more than actual number of children, the number of extra-children – a variable that is created by deducting a woman's desired number of children from her actual number of children – has a more robust impact on labor market outcomes. Then we estimate the extent of motherhood-penalty across different cultural values pertaining to different societies, families and occupations and find that the degree of labor market penalty varies with different cultural settings and also with wealth positions. We also do robustness check with different measures of motherhood which confirms the existence of labor market penalty irrespective of how we measure motherhood.

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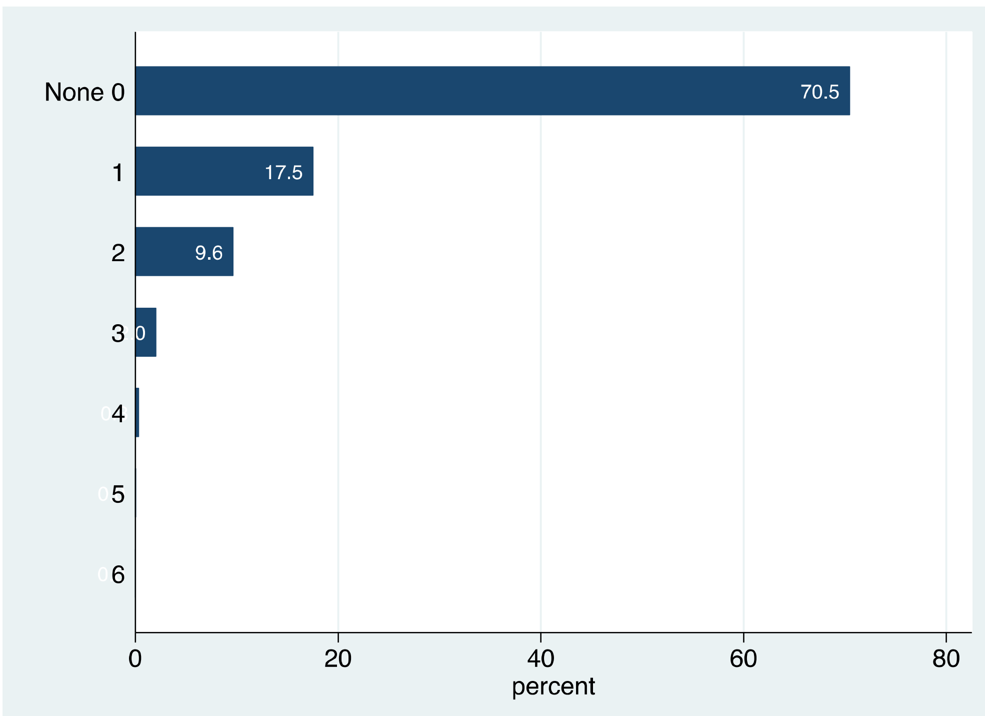

Figure 1: Distribution of children conceived between since Jan, 2005 (From IHDS 2)

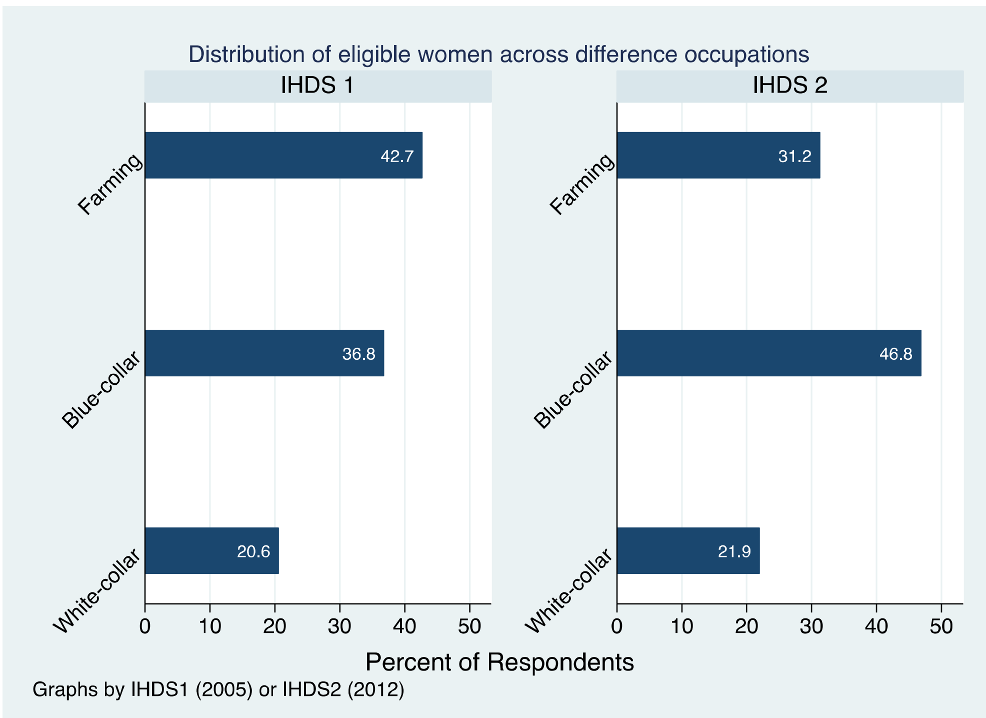

Figure 2: Distribution of eligible women across different occupational groups (IHDS 1 and 2).

Tables:

	IHDS1			IHDS2		
Variable	N	Mean	SD	N	Mean	SD
A. Motherhood related variables:						
Motherhood status	25413	.934	.248	21240	.979	.142
Number of children	25413	2.681	1.577	21240	2.895	1.417
Extra children	25413	.258	1.424	20303	.42	1.26
B. Work related variables						
Work Hours	7831	1238.911	732.685	9095	1183.378	828.676
Hourly Wage (in Rs)	7528	12.5	16.228	8056	17.738	21.191
Whether employed	33782	.415	.493	28342	.481	.5
Whether Full time job	33782	.075	.263	28342	.097	.296
Whether Part time job	33782	.34	.474	28342	.384	.486
C. Other controls						
Age	25479	33.205	7.91	21243	37.936	6.567
Household size	33782	6.299	3.077	28342	5.615	2.653
Education in years	25475	4.231	4.658	21243	4.533	4.681

Table 1: Descriptive statistics

	(1) Wage	(2) Work_Hr	(3) Employed	(4) Full_time	(5) Part_time
Number of children	-.03499*	-.02882	-.00893**	-.00451	-.00442
	(.01849)	(.02072)	(.00447)	(.00296)	(.00463)
age	.07784***	-.00451	.09242***	.02302***	.0694***
	(.00907)	(.01023)	(.0023)	(.00152)	(.00238)
Age sq	-.00054***	-.00011	-.00127***	-.0003***	-.00097***
	(.00011)	(.00013)	(.00003)	(.00002)	(.00003)
0bn.edu_yr					
1.edu_yr	-.03421	-.05613	-.00124	.00052	-.00176
	(.04274)	(.04833)	(.01111)	(.00736)	(.01151)
2.edu_yr	-.07265	-.02226	-.03229**	.00425	-.03654**
	(.0739)	(.08385)	(.01443)	(.00957)	(.01495)
3.edu_yr	-.01493	.20682	-.00349	.01647	-.01995
	(.14415)	(.16523)	(.02416)	(.01601)	(.02503)
4.edu_yr	.10639	.21782	.09161***	.09229***	-.00067
	(.1541)	(.17671)	(.0309)	(.02048)	(.03201)
0bn.occu_nic					
1.occu_nic	.08217***	-.11517***			
	(.02854)	(.03185)			
2.occu_nic	-.00345	.31146***			
	(.05502)	(.06178)			

HH size	-.01064	-.00741	-.00741***	-.00288***	-.00452***
	(.00681)	(.0077)	(.00153)	(.00101)	(.00158)
1bn.ASSETS5					
2.ASSETS5	.0575**	.00844	-.01371	-.01264**	-.00107
	(.0286)	(.032)	(.00962)	(.00637)	(.00997)
3.ASSETS5	.10511***	-.0907**	-.03835***	-.01667**	-.02168*
	(.03518)	(.03987)	(.01119)	(.00742)	(.0116)
4.ASSETS5	.1072**	-.08126	-.06385***	-.02843***	-.03542**
	(.05016)	(.05694)	(.01334)	(.00884)	(.01382)
5.ASSETS5	.24664***	-.10419	-.06873***	-.02813***	-.04059**
	(.09084)	(.1041)	(.0159)	(.01053)	(.01647)
_cons	.356**	7.28291***	-1.04932***	-.29012***	-.7592***
	(.17162)	(.19317)	(.04309)	(.02856)	(.04464)
Observations	14016	14402	50768	50768	50768
R-squared	.12515	.03172	.09186	.01345	.05309

Standard errors are in parentheses

**** p<.01, ** p<.05, * p<.1*

Table 2: Baseline regression with number of children as measure of motherhood

	(1)	(2)	(3)	(4)	(5)
	Wage	Work_Hr	Employed	Full_time	Part_time
Extra children	-.03161***	-.02358**	-.00881***	-.00022	-.00858***
	(.01078)	(.01199)	(.00279)	(.00186)	(.0029)
age	.07887***	-.00836	.09109***	.02226***	.06883***
	(.00936)	(.01042)	(.00226)	(.0015)	(.00234)
Age sq	-.00057***	-.00003	-.00126***	-.00029***	-.00096***
	(.00012)	(.00013)	(.00003)	(.00002)	(.00003)
0bn.edu_yr					
1.edu_yr	-.04592	-.06743	-.01036	-.00525	-.00511
	(.04568)	(.051)	(.01175)	(.00781)	(.01219)
2.edu_yr	-.07792	-.01405	-.04145***	.00319	-.04464***
	(.07897)	(.08838)	(.01529)	(.01016)	(.01586)
3.edu_yr	.00967	.24896	-.01032	.00633	-.01664
	(.15493)	(.17538)	(.02554)	(.01697)	(.02649)
4.edu_yr	.09193	.24554	.08759***	.0905***	-.00291
	(.16684)	(.18895)	(.03272)	(.02174)	(.03393)
0bn.occu_nic					
1.occu_nic	.08096***	-.15493***			
	(.03109)	(.03431)			
2.occu_nic	.00648	.30507***			
	(.0602)	(.06697)			
HH size	-.0128*	-.00658	-.00769***	-.00358***	-.0041**
	(.00723)	(.00809)	(.0016)	(.00106)	(.00166)

1bn.ASSETS5					
2.ASSETS5	.06421**	.01366	-.01984*	-.01462**	-.00522
	(.03073)	(.034)	(.01022)	(.00679)	(.0106)
3.ASSETS5	.08584**	-.08056*	-.04332***	-.01695**	-.02637**
	(.03795)	(.0425)	(.01189)	(.0079)	(.01233)
4.ASSETS5	.10424*	-.07927	-.06956***	-.0276***	-.04196***
	(.05442)	(.06105)	(.01415)	(.0094)	(.01467)
5.ASSETS5	.28671***	-.09164	-.07597***	-.028**	-.04797***
	(.09948)	(.11263)	(.01681)	(.01117)	(.01743)
_cons	.2793	7.2349***	-1.03428***	-.28559***	-.74869***
	(.18817)	(.20912)	(.04608)	(.03062)	(.04778)
Observations	13144	13508	47853	47853	47853
R-squared	.1223	.03114	.08791	.01334	.05087

Standard errors are in parentheses

**** p<.01, ** p<.05, * p<.1*

Table 3: Baseline regression with number of extra children as measure of motherhood

	(1) Wage	(2) WP	(3) Employed	(4) Full	(5) Part
Extra Children	-.04651***	-.05835***	-.01205***	-.00417*	-.00788**
	(.01441)	(.01585)	(.00328)	(.00218)	(.0034)
Extra Children*South	.03262	.07801***	.01101*	.01338***	-.00237
	(.02094)	(.02329)	(.00582)	(.00387)	(.00604)
age	.07957***	-.00666	.0912***	.02238***	.06881***
	(.00936)	(.01042)	(.00226)	(.0015)	(.00235)
Age sq	-.00057***	-.00005	-.00126***	-.00029***	-.00096***
	(.00012)	(.00013)	(.00003)	(.00002)	(.00003)
0bn.edu_yr					
1.edu_yr	-.04361	-.06259	-.01001	-.00483	-.00518
	(.0457)	(.05095)	(.01175)	(.00781)	(.01219)
2.edu_yr	-.07865	-.01658	-.04112***	.00359	-.04471***
	(.07895)	(.08826)	(.01529)	(.01016)	(.01586)
3.edu_yr	.01139	.2523	-.01003	.00668	-.01671
	(.15491)	(.17514)	(.02554)	(.01697)	(.02649)
4.edu_yr	.09248	.24611	.08827***	.09132***	-.00306
	(.16681)	(.18869)	(.03272)	(.02174)	(.03393)
0bn.occu_nic					
1.occu_nic	.08051***	-.15504***			
	(.03108)	(.03426)			
2.occu_nic	.00769	.30708***			
	(.06019)	(.06688)			

HH size	-.01254*	-.00571	-.00764***	-.00353***	-.00411**
	(.00724)	(.00808)	(.0016)	(.00106)	(.00166)
1bn.ASSETS5					
2.ASSETS5	.06224**	.0085	-.02046**	-.01537**	-.00509
	(.03075)	(.03399)	(.01022)	(.00679)	(.0106)
3.ASSETS5	.08393**	-.08535**	-.04395***	-.01771**	-.02624**
	(.03796)	(.04247)	(.0119)	(.0079)	(.01234)
4.ASSETS5	.10333*	-.08194	-.0701***	-.02825***	-.04185***
	(.05441)	(.06097)	(.01415)	(.0094)	(.01468)
5.ASSETS5	.28795***	-.08934	-.07655***	-.02871**	-.04784***
	(.09946)	(.11248)	(.01681)	(.01117)	(.01743)
_cons	.26548	7.20032***	-1.03592***	-.28759***	-.74834***
	(.18834)	(.20909)	(.04609)	(.03062)	(.04779)
Observations	13144	13508	47853	47853	47853
R-squared	.12289	.03407	.08806	.01386	.05088

Standard errors are in parentheses

**** p<.01, ** p<.05, * p<.1*

Table 4: Heterogeneity analysis: Southern states vs rest of India

	(1)	(2)	(3)	(4)	(5)
	Wage	WP	Employed	Full	Part
Extra Children	-.03147***	-.02783**	-.01023***	-.00081	-.00942***
	(.01144)	(.01269)	(.00315)	(.00209)	(.00326)
Extra Children*Urban	-.00116	.03732	.00609	.00252	.00357
	(.03247)	(.0366)	(.00623)	(.00414)	(.00646)
age	.07886***	-.00809	.09107***	.02225***	.06882***
	(.00936)	(.01042)	(.00226)	(.0015)	(.00234)
Age sq	-.00057***	-.00004	-.00126***	-.00029***	-.00096***
	(.00012)	(.00013)	(.00003)	(.00002)	(.00003)
0bn.edu_yr					
1.edu_yr	-.04593	-.06702	-.01043	-.00528	-.00515
	(.04569)	(.051)	(.01175)	(.00781)	(.01219)
2.edu_yr	-.078	-.01162	-.04143***	.0032	-.04463***
	(.07901)	(.08841)	(.01529)	(.01016)	(.01586)
3.edu_yr	.00963	.25012	-.0102	.00637	-.01658
	(.15496)	(.17538)	(.02554)	(.01697)	(.02649)
4.edu_yr	.09187	.24725	.08781***	.0906***	-.00278
	(.16688)	(.18896)	(.03272)	(.02174)	(.03393)
0bn.occu_nic					
1.occu_nic	.08094***	-.15438***			
	(.0311)	(.03432)			
2.occu_nic	.00651	.3046***			
	(.06021)	(.06697)			

HH size	-.0128*	-.00666	-.0077***	-.00359***	-.00411**
	(.00724)	(.00809)	(.0016)	(.00106)	(.00166)
1bn.ASSETS5					
2.ASSETS5	.06422**	.01311	-.02008**	-.01472**	-.00537
	(.03074)	(.034)	(.01022)	(.00679)	(.0106)
3.ASSETS5	.08589**	-.08228*	-.04367***	-.0171**	-.02657**
	(.03798)	(.04253)	(.0119)	(.00791)	(.01234)
4.ASSETS5	.1043*	-.0812	-.06991***	-.02774***	-.04216***
	(.05444)	(.06108)	(.01416)	(.00941)	(.01468)
5.ASSETS5	.28675***	-.09318	-.07622***	-.0281**	-.04812***
	(.0995)	(.11264)	(.01681)	(.01117)	(.01743)
_cons	.27947	7.2293***	-1.03364***	-.28532***	-.74832***
	(.18826)	(.20919)	(.04609)	(.03062)	(.04779)
Observations	13144	13508	47853	47853	47853
R-squared	.1223	.03142	.08795	.01336	.05088

Standard errors are in parentheses

**** p<.01, ** p<.05, * p<.1*

Table 5: Heterogeneity analysis: Rural vs Urban

	(1) Wage	(2) WP	(3) Employed	(4) Full	(5) Part
Extra Children	-.01487	-.0451**	-.0078**	-.00448*	-.00332
	(.02053)	(.02252)	(.00366)	(.00243)	(.00379)
Extra Ch*High WLFPR	-.02259	.02933	-.00226	.00955***	-.01181**
	(.02358)	(.02599)	(.00531)	(.00353)	(.0055)
age	.07863***	-.00816	.09108***	.0223***	.06878***
	(.00936)	(.01042)	(.00226)	(.0015)	(.00234)
Age sq	-.00056***	-.00003	-.00126***	-.00029***	-.00096***
	(.00012)	(.00013)	(.00003)	(.00002)	(.00003)
0bn.edu_yr					
1.edu_yr	-.04698	-.06603	-.01045	-.00485	-.0056
	(.0457)	(.05101)	(.01175)	(.00781)	(.01219)
2.edu_yr	-.078	-.01424	-.04155***	.00362	-.04517***
	(.07897)	(.08837)	(.01529)	(.01016)	(.01586)
3.edu_yr	.00892	.24966	-.01043	.00679	-.01722
	(.15494)	(.17537)	(.02555)	(.01697)	(.02649)
4.edu_yr	.09253	.24454	.08741***	.09126***	-.00385
	(.16685)	(.18895)	(.03272)	(.02174)	(.03393)
0bn.occu_nic					
1.occu_nic	.08178***	-.15599***			
	(.0311)	(.03432)			
2.occu_nic	.00596	.30547***			
	(.0602)	(.06697)			
NPERSONS	-.01303*	-.0063	-.00769***	-.00355***	-.00414**

	(.00724)	(.00809)	(.0016)	(.00106)	(.00166)
1bn.ASSETS5					
2.ASSETS5	.06491**	.01276	-.01974*	-.01503**	-.00471
	(.03074)	(.03401)	(.01022)	(.00679)	(.0106)
3.ASSETS5	.08658**	-.08149*	-.04322***	-.01739**	-.02583**
	(.03796)	(.04251)	(.01189)	(.0079)	(.01233)
4.ASSETS5	.10471*	-.0798	-.06945***	-.02809***	-.04136***
	(.05442)	(.06105)	(.01415)	(.0094)	(.01468)
5.ASSETS5	.28821***	-.0935	-.07584***	-.02854**	-.04731***
	(.09949)	(.11264)	(.01681)	(.01117)	(.01743)
_cons	.28264	7.23278***	-1.03416***	-.28607***	-.7481***
	(.1882)	(.20912)	(.04608)	(.03062)	(.04778)
Observations	13144	13508	47853	47853	47853
R-squared	.12252	.03148	.08792	.01366	.05106

Standard errors are in parentheses

**** p<.01, ** p<.05, * p<.1*

Table 6: Heterogeneity analysis: High vs Low WLFPR states

	(1)	(2)	(3)	(4)	(5)
	Wage	WP	Employed	Full	Part
Extra Children	-.01466	-.07886***	-.01558***	-.0065***	-.00908**
	(.01423)	(.01568)	(.00351)	(.00233)	(.00364)
Extra Ch*High Sex ratio	-.03825*	.12657***	.01719***	.01593***	.00126
	(.02099)	(.02327)	(.00541)	(.0036)	(.00561)
Age	.07859***	-.00777	.09121***	.02237***	.06884***
	(.00935)	(.01038)	(.00226)	(.0015)	(.00234)
Age sq	-.00057***	-.00003	-.00126***	-.00029***	-.00096***
	(.00012)	(.00013)	(.00003)	(.00002)	(.00003)
0bn.edu_yr					
1.edu_yr	-.04711	-.06354	-.00986	-.00479	-.00507
	(.04567)	(.05081)	(.01175)	(.00781)	(.01219)
2.edu_yr	-.07725	-.01586	-.04131***	.00332	-.04463***
	(.07894)	(.08804)	(.01529)	(.01016)	(.01586)
3.edu_yr	.00707	.25761	-.00942	.00715	-.01658
	(.15489)	(.17471)	(.02554)	(.01697)	(.02649)
4.edu_yr	.09053	.25041	.08803***	.09091***	-.00288
	(.16679)	(.18823)	(.03271)	(.02173)	(.03393)
0bn.occu_nic					
1.occu_nic	.08038***	-.15332***			
	(.03108)	(.03418)			
2.occu_nic	.00617	.30738***			
	(.06018)	(.06671)			
HH size	-.01247*	-.00757	-.00772***	-.00362***	-.00411**

	(.00723)	(.00806)	(.0016)	(.00106)	(.00166)
1bn.ASSETS5					
2.ASSETS5	.06273**	.01804	-.02075**	-.01546**	-.00529
	(.03073)	(.03388)	(.01022)	(.00679)	(.0106)
3.ASSETS5	.08371**	-.07314*	-.0438***	-.01739**	-.02641**
	(.03796)	(.04236)	(.01189)	(.0079)	(.01233)
4.ASSETS5	.10327*	-.07633	-.06986***	-.02787***	-.04198***
	(.0544)	(.06082)	(.01415)	(.0094)	(.01467)
5.ASSETS5	.28625***	-.09035	-.07615***	-.02817**	-.04798***
	(.09945)	(.1122)	(.01681)	(.01116)	(.01743)
_cons	.28721	7.21336***	-1.03625***	-.28741***	-.74884***
	(.18816)	(.20835)	(.04608)	(.03061)	(.04779)
Observations	13144	13508	47853	47853	47853
R-squared	.12311	.03884	.08832	.0142	.05087

Standard errors are in parentheses

**** p<.01, ** p<.05, * p<.1*

Table 7: Heterogeneity analysis: High vs Low sex-ratio states

	(1)	(2)	(3)	(4)	(5)
	Wage	WP	Employed	Full	Part
Extra Children	-.04591**	-.05224**	-.00856	.0007	-.00926
	(.01982)	(.0221)	(.00566)	(.00376)	(.00587)
Extra Children*Asset	.00738	.01481	-.00009	-.00033	.00025
	(.00859)	(.0096)	(.00179)	(.00119)	(.00185)
1bn.ASSETS5					
2.ASSETS5	.06097**	.00701	-.01978*	-.01441**	-.00537
	(.03096)	(.03427)	(.01028)	(.00683)	(.01066)
3.ASSETS5	.07998**	-.09256**	-.04324***	-.01662**	-.02661**
	(.03856)	(.0432)	(.01202)	(.00799)	(.01247)
4.ASSETS5	.09657*	-.09511	-.06944***	-.02715***	-.04229***
	(.05514)	(.0619)	(.01436)	(.00954)	(.01489)
5.ASSETS5	.27648***	-.11265	-.07582***	-.02744**	-.04838***
	(.10019)	(.11343)	(.01707)	(.01135)	(.0177)
Age	.07874***	-.00858	.0911***	.02227***	.06882***
	(.00936)	(.01042)	(.00226)	(.0015)	(.00235)
Age sq	-.00056***	-.00003	-.00126***	-.00029***	-.00096***
	(.00012)	(.00013)	(.00003)	(.00002)	(.00003)
0bn.edu_yr					
1.edu_yr	-.04559	-.0667	-.01036	-.00525	-.0051
	(.04569)	(.05099)	(.01175)	(.00781)	(.01219)
2.edu_yr	-.07864	-.01525	-.04145***	.00321	-.04466***
	(.07898)	(.08836)	(.01529)	(.01016)	(.01586)

3.edu_yr	.00729	.2444	-.01032	.00632	-.01664
	(.15497)	(.17537)	(.02554)	(.01697)	(.02649)
4.edu_yr	.08875	.23936	.08759***	.09051***	-.00292
	(.16689)	(.18896)	(.03272)	(.02174)	(.03393)
0bn.occu_nic					
1.occu_nic	.08115***	-.15428***			
	(.03109)	(.03431)			
2.occu_nic	.0073	.30675***			
	(.06021)	(.06697)			
HH size	-.01274*	-.00637	-.00769***	-.00359***	-.0041**
	(.00724)	(.00809)	(.0016)	(.00106)	(.00166)
_cons	.28344	7.24188***	-1.03442***	-.28612***	-.7483***
	(.18824)	(.20913)	(.04617)	(.03068)	(.04787)
Observations	13144	13508	47853	47853	47853
R-squared	.12248	.03177	.08791	.01334	.05087

Standard errors are in parentheses

**** p<.01, ** p<.05, * p<.1*

Table 8: Heterogeneity analysis: Family wealth-based classification

	(1)	(2)	(3)	(4)	(5)
	Wage	WP	Employed	Full	Part
Extra Children	-.03986**	-.008	.0004	-.00039	.00079
	(.01975)	(.02168)	(.00483)	(.0032)	(.005)
Extra Ch*Other's say	.00494	-.02312	-.01066**	.00044	-.0111**
	(.0207)	(.02263)	(.00488)	(.00323)	(.00506)
Other's say	.00457	.08551***	-.01242*	.00126	-.01368*
	(.02811)	(.03129)	(.00681)	(.00452)	(.00706)
age	.07819***	-.00407	.0893***	.02171***	.06759***
	(.00985)	(.01092)	(.00234)	(.00155)	(.00243)
agesq	-.00055***	-.00006	-.00123***	-.00028***	-.00095***
	(.00013)	(.00014)	(.00003)	(.00002)	(.00003)
0bn.edu_yr					
1.edu_yr	-.0457	-.03724	-.01005	-.00212	-.00793
	(.04804)	(.05344)	(.01215)	(.00805)	(.0126)
2.edu_yr	-.06235	-.04701	-.03971**	.00285	-.04255***
	(.08438)	(.09384)	(.01573)	(.01043)	(.01631)
3.edu_yr	-.03432	.25713	-.00948	.00898	-.01846
	(.16374)	(.18432)	(.02612)	(.01731)	(.02709)
4.edu_yr	.03781	.26393	.08502**	.08301***	.00201
	(.17729)	(.19967)	(.03344)	(.02216)	(.03467)
0bn.occu_nic					
1.occu_nic	.08273**	-.15642***			
	(.03232)	(.03555)			
2.occu_nic	-.01506	.23644***			
	(.06314)	(.0702)			

NPERSONS	-.01189	-.00667	-.00733***	-.00335***	-.00398**
	(.00764)	(.00849)	(.00166)	(.0011)	(.00172)
1bn.ASSETS5					
2.ASSETS5	.06336*	.02442	-.01945*	-.01486**	-.00458
	(.03259)	(.03589)	(.01061)	(.00703)	(.011)
3.ASSETS5	.07791*	-.07411*	-.04267***	-.01725**	-.02542**
	(.03988)	(.0444)	(.01233)	(.00817)	(.01278)
4.ASSETS5	.09283	-.07305	-.06828***	-.02693***	-.04135***
	(.05723)	(.0639)	(.01468)	(.00973)	(.01522)
5.ASSETS5	.26833***	-.09617	-.0758***	-.02774**	-.04806***
	(.10224)	(.11515)	(.01739)	(.01152)	(.01803)
_cons	.28706	7.05793***	-.99616***	-.27983***	-.71634***
	(.19995)	(.22116)	(.04827)	(.03199)	(.05005)
Observations	12606	12951	46247	46247	46247
R-squared	.12138	.02905	.08408	.01252	.04885

Standard errors are in parentheses

**** p<.01, ** p<.05, * p<.1*

Table 9: Heterogeneity analysis: classification based on female autonomy in the family

	(1)	(2)	(3)	(4)	(5)
	Wage	Work_Hours	Employment	Full_time	Part_time
0bn.child_d					
1.child_d	-.02207	-.04963	-.06122***	-.01902*	-.0422**
	(.08553)	(.09516)	(.0172)	(.01141)	(.01783)
2.child_d	-.02178	-.07784	-.10532***	-.02451**	-.08082***
	(.08568)	(.09502)	(.01751)	(.01162)	(.01815)
3.child_d	-.15496*	-.14342	-.10602***	-.02771**	-.07831***
	(.09299)	(.10384)	(.02005)	(.0133)	(.02078)
4.child_d	-.14213	-.19694*	-.09584***	-.0357**	-.06014**
	(.10525)	(.11739)	(.02323)	(.01541)	(.02408)
5.child_d	-.24791**	-.19926	-.05634**	-.03616**	-.02018
	(.11716)	(.13092)	(.02728)	(.0181)	(.02828)
Age	.07961***	-.00189	.0962***	.02366***	.07254***
	(.00925)	(.01046)	(.00237)	(.00157)	(.00246)
Age sq	- .00056***	-.00014	-.00132***	-.00031***	-.00101***
	(.00011)	(.00013)	(.00003)	(.00002)	(.00003)
0bn.edu_yr					
1.edu_yr	-.03143	-.05603	-.00024	.00066	-.0009
	(.04275)	(.04837)	(.0111)	(.00736)	(.0115)
2.edu_yr	-.07416	-.02364	-.03104**	.0044	-.03544**
	(.07388)	(.08387)	(.01442)	(.00957)	(.01495)
3.edu_yr	-.01512	.20682	-.00314	.01649	-.01964
	(.14413)	(.16531)	(.02414)	(.01601)	(.02502)
4.edu_yr	.1068	.21868	.09201***	.09221***	-.00021

	(.15406)	(.17676)	(.03087)	(.02048)	(.032)
0bn.occu_nic					
1.occu_nic	.08129***	-.11492***			
	(.02854)	(.03187)			
2.occu_nic	-.00386	.31185***			
	(.05502)	(.06182)			
NPERSONS	-.00983	-.00655	-.00701***	-.00276***	-.00425***
	(.00681)	(.0077)	(.00153)	(.00101)	(.00158)
1bn.ASSETS5					
2.ASSETS5	.05772**	.0069	-.01366	-.01281**	-.00085
	(.02862)	(.03204)	(.00961)	(.00638)	(.00996)
3.ASSETS5	.10267***	-.09226**	-.03929***	-.01695**	-.02234*
	(.03518)	(.03989)	(.01118)	(.00742)	(.01159)
4.ASSETS5	.10497**	-.0832	-.06568***	-.02891***	-.03677***
	(.05014)	(.05697)	(.01333)	(.00884)	(.01381)
5.ASSETS5	.24568***	-.10724	-.0713***	-.02873***	-.04257***
	(.09082)	(.10414)	(.01588)	(.01054)	(.01646)
_cons	.32013*	7.26833***	-1.06263***	-.28934***	-.77329***
	(.18015)	(.20236)	(.04444)	(.02948)	(.04605)
Observations	14016	14402	50768	50768	50768
R-squared	.12676	.03222	.0935	.01359	.05433

Standard errors are in parentheses

**** $p<.01$, ** $p<.05$, * $p<.1$*

Table 10: Robustness check: dummy for the number of children

	(1)	(2)	(3)	(4)	(5)
	Wage	Work_Hr	Employed	Full_time	Part_time
Motherhood dummy	-.03064	-.0657	-.08454***	-.0211*	-.06344***
	(.08136)	(.09016)	(.01628)	(.0108)	(.01687)
age	.07201***	-.00843	.09367***	.02278***	.07089***
	(.0086)	(.00969)	(.00213)	(.00141)	(.00221)
Age sq	-.00048***	-.00007	-.00129***	-.0003***	-.00099***
	(.00011)	(.00012)	(.00003)	(.00002)	(.00003)
0bn.edu_yr					
1.edu_yr	-.03421	-.05599	-.00092	.00058	-.0015
	(.04276)	(.04834)	(.0111)	(.00736)	(.01151)
2.edu_yr	-.07188	-.02155	-.03187**	.00434	-.03621**
	(.07393)	(.08386)	(.01443)	(.00957)	(.01495)
3.edu_yr	-.01834	.20288	-.00335	.01656	-.01991
	(.14423)	(.16528)	(.02415)	(.01601)	(.02502)
4.edu_yr	.10346	.21497	.09109***	.09218***	-.00109
	(.15417)	(.17674)	(.03088)	(.02048)	(.032)
0bn.occu_nic					
1.occu_nic	.0807***	-.11656***			
	(.02854)	(.03184)			
2.occu_nic	-.00287	.31125***			
	(.05505)	(.0618)			
NPERSONS	-.01345**	-.00941	-.0072***	-.00299***	-.00421***
	(.00665)	(.00751)	(.0015)	(.001)	(.00156)
1bn.ASSETS5					

2.ASSETS5	.05943**	.0098	-.01365	-.01234*	-.00131
	(.0286)	(.03199)	(.0096)	(.00637)	(.00995)
3.ASSETS5	.1102***	-.08671**	-.0386***	-.01628**	-.02232*
	(.03509)	(.03974)	(.01116)	(.0074)	(.01157)
4.ASSETS5	.11405**	-.07667	-.06491***	-.02811***	-.03679***
	(.05007)	(.05682)	(.0133)	(.00882)	(.01378)
5.ASSETS5	.25444***	-.09931	-.07009***	-.02781***	-.04229**
	(.09081)	(.10404)	(.01585)	(.01051)	(.01643)
_cons	.41963**	7.35484***	-1.01885***	-.27679***	-.74206***
	(.17361)	(.19444)	(.0416)	(.02758)	(.04311)
Observations	14016	14402	50768	50768	50768
R-squared	.12441	.0314	.09268	.01351	.05359

Standard errors are in parentheses

**** p<.01, ** p<.05, * p<.1*

Table 11: Robustness check: dummy for motherhood.