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ABSTRACT

This paper presents evidence on intergenerational occupational mobility from agriculture to the nonfarm sector using survey data from Nepal with a focus on the role played by cultural inheritance and gender norms. In the absence of credible instruments, the degree of selection on observables is used as a guide to the degree of selection on unobservables á la Altonji et. al. (2005) to address the unobserved genetic correlations. The results show that cultural inheritance plays a causal role in intergenerational occupational correlation between the mother and daughter. In contrast, there is no robust evidence that cultural inheritance is important for sons' occupation choice. A moderate genetic correlation can easily explain away the estimated partial correlation in non-farm participation between the father and a son.

Keywords: Intergenerational Occupational Correlations, Non-Farm Participation, Gender effect, Cultural Inheritance, Selection on Observables, Selection on Unobservables

JEL Codes: J62, O12

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(1) Introduction

The evolution of income distribution, inequality and occupational structure across generations has attracted increasing attention in recent economic literature.[1] This renewed interest reflects a widely shared view that strong intergenerational linkages in socioeconomic status may reflect inequality of opportunities and thus have profound implications for poverty, inequality and (im)mobility in a society. A large body of econometric studies focusing mainly on developed countries finds that intergenerational correlations in *earnings* are positive and statistically significant, ranging between 0.14 to 0.50 (see Blanden et. al. (2005) and Solon (1999, 2002)). There is a (relatively) small empirical literature in economics, again mostly in the context of developed countries, that indicates significant positive correlations between parents and their children in occupational choices (see, for example, Lentz and Laband (1983), and Dunn and Holtz-Eakin (2000) on U.S and Sjogren (2000) on Sweden). Economic analysis of intergenerational mobility in developing countries, however, remains a relatively unexplored terrain,[2] even though the importance of such analysis has been duly recognized in the recent literature.[3] In this paper, we present evidence on the intergenerational occupational linkages in the non-farm sector in a developing

[1]See, for example, Arrow et al. (2000), Dearden et. al. (1997), Mulligan (1999), Solon (1999, 2002), Birdsall and Graham (1999), Fields (2001), Fields et. al. (2005), Bowles et. al. (2005), Blanden et. al. (2005), WDR (2005), Mazumder (2005), Hertz (2005), Mookherjee and Ray (2006), Bjorklund et. al. (2006).

[2]This is exemplified by the fact that Solon (2002) refers to only two studies on developing countries in his survey of economic mobility (Lillard and Kilburn (1995) on Malaysia, and Hertz (2001) on South Africa). The recent analysis of economic mobility in the context of developing countries include Lam and Schoeni (1993), Behrman et. al. (2001), Fields et. al. (2005), Dunn (2004). There is, however, a substantial sociological literature that analyzes occupational mobility in both developed and developing countries (see, Ganzeboom et. al. (1991), Morgan, (2005)).

[3]For example, Bardhan (2005) identifies intergenerational economic mobility as one of the important but under-researched areas in development economics.

country, Nepal.[4] Our focus in this paper is on two issues: (*i*) intergenerational occupational persistence beyond both the observed determinants like education and assets, and the unobserved genetic correlations, and (*ii*) gender differences in occupational mobility. As discussed in the theoretical literature on economic mobility, there are many causal processes at work behind the observed intergenerational correlations in socio-economic status. They include (*i*) conscious investments by parents like human capital investment, and (*ii*) cultural inheritance that include role model effects and learning and reputation externalities (Becker and Tomes, 1979, 1986, Solon, 2004, Bjorklund et. al. 2007).[5] The role played by cultural inheritance has, however, not received adequate attention in the economic literature on intergenerational mobility. We provide evidence that cultural inheritance might play a causal role in occupational linkages across generations for daughters in Nepal, but find little evidence of such effects in case of sons.

There might be important gender differences in the role cultural inheritance plays in occupation choices, especially in developing countries where cultural norms usually constrain women's social and economic interactions (Collier, 1988, World Bank, 2001). Since the domain of social interaction for women in a traditional society is limited mostly within and around the household, it is likely that the influence of parents, especially mothers, on their choices will be much more pronounced. This might give rise to significant role model

[4] As emphasized by Goldberger (1989), there are some important advantages to focusing on occupational mobility rather than income mobility. For example, the intergenerational linkages might be stronger for occupation choice (relative to income), and focusing on income correlations "could lead an economist to understate the influence of family background on inequality" (P.513).

[5] The distinction related to whether parental investment is conscious or not may, however, be overdrawn. In the context of occupational choice one important part of cultural inheritance of children is the informal apprenticeship under the tutelage of the parents. The informal apprenticeship is a conscious investment decision by the parents in terms of their time allocation.

effects for daughters.[6] In contrast, men in most of the developing countries have much more freedom in social and economic interactions, and thus the set of role models is much richer and also learning externalities may be more diffused. This is likely to weaken the effects of the parents, especially fathers, on the choices of sons including their choice of occupations. The empirical results reported in this paper provide evidence consistent with such gender differences in cultural inheritance in a traditional rural society, Nepal. Nepal is an interesting case study to understand the gender differences as there are strong social and cultural norms regarding gender roles that work against women's economic mobility (for more details, please see P. 12).

The literature on the intergenerational economic mobility has been fraught with econometric challenges that arise from the unobservability of the genetic characteristics (ability and preference transmissions across generations), and the partial correlations observed in the data (from multivariate regressions) might be driven largely by such unobserved genetic correlations between parents and children.[7] In the absence of experimental data,[8] the standard approach to identification when facing unobserved heterogeneity like ability correlations is to look for credible instrumental variables (IV). In the specific context of

[6]Bevan et. al. (1986) provide preliminary evidence that role model effects are important in the choice of crops and occupation choice of women in rural Africa.

[7]Genetic transmissions relevant for occupational choice include both ability and preference (especially the degree of risk aversion). However, the focus of the literature has been on ability correlations. In what follows, we couch the discussion primarily in terms of ability correlations, following the literature.

We, however, note that one should not take the distinction between genetic transmissions and other environmental factors too far. The evidence from Behavioral Genetics shows that there may be significant dynamic interactions between nature and nurture in determining human behavior (see, for example, Plomin et. al. (2001), Boyd and Richerson, 1985).

[8]Designing and implementing a randomized experiment that can generate the data required for understanding the intergenerational occupational persistence can be challenging on both ethical and feasibility grounds.

occupational mobility, the econometric challenge is to find exogenous variation that affects parental occupation choice but does not have any independent effect on children's occupation choice. However, most of the potential candidates for IV such as family background variables that affect parent's occupation choice tend to affect children's choice also. Thus it is difficult to defend the exclusion restriction. Moreover, the common practice of using parental characteristics (like parental education) as IVs is also suspect, as they are likely to be correlated with the unobserved common ability subsumed in the error term, and thus likely to violate the exogeneity criterion. There is a small literature in economics that uses adoption as a quasi-experimental design to isolate the effects of environmental factors in intergenerational economic mobility (see, for example, Bjorklund et. al. (2006); Plug (2004); Plug and Vijverberg (2003), Scaerdote (2002)). A third strategy is to use twin samples to try to isolate the effects of nurture from that of nature (see, for example, Behrman and Rosenzweig (2002)). However, these studies using adoption or twin samples are confined mostly in the developed countries where such data of reliable quality are available. In the absence of quasi-experimental data on adoptions and twins or any credible identifying instruments, we exploit the econometric methodology recently developed by Altonji, Elder and Taber (2005, 2000) (henceforth AET (2005, 2000)) which provides a way to gauge the importance of unobserved genetic transmissions in explaining an observed partial correlation. This helps to determine if at least part of the observed partial correlation is causal due to environmental factors like cultural inheritance. We note that genetic transmissions (ability and preference) influence both parents' and children's nonfarm participation decisions and hence can be treated as an unobserved correlated determinant of nonfarm employment choices of both generations. This allows us to utilize a battery of recently developed econometric tests to ascertain whether the observed intergenerational occupational correlations can be attributed solely to the unobserved ability correlations between children and their parents.

The results from the econometric analysis are as follows. The univariate probit estimation indicates the presence of strong and positive intergenerational occupational correlations along gender lines (mother-daughter and father-son) even after controlling for a rich set of regressors including education (own, parents' and spouse's), assets (inherited land), age and ethnicity (caste/tribe). The estimated occupational linkages from univariate probit can, however, at least in principle, be due entirely to genetic transmissions across generations rather than cultural inheritance. The evidence from the econometric analysis using the AET (2005) methodology shows that this might actually be the case for the observed occupational correlation between the father and son; even a moderate correlation of unobserved ability can explain away the estimated occupational linkage completely. The intergenerational occupational correlation between mother and daughter, on the other hand, is very strong and unlikely to be driven solely by unobserved genetic correlations. The evidence thus suggests that at least part of the correlation between mother and daughter is likely to be causal due to cultural inheritance that includes role model effects, apprenticeship externalities and transfer of reputation and social capital from parents to children.

The substantive conclusions above are very robust, confirmed by alternative econometric techniques as developed by AET (2005. 2000): (i) sensitivity analysis using a bivariate probit model, and (ii) estimates of lower bounds on intergenerational occupational correlations.[9] In case of daughters, the lower bound estimate of intergenerational occupational correlation with mother is 0.66 with an implied marginal effect of 0.14 and t-value of 4.8. The 95 percent confidence interval for the marginal effect is [0.07 0.24], which *does not* include zero. These results suggest that the genetic correlations account for about half of the partial correlation between the mother and a daughter given that the marginal effect in the univariate probit model is 0.30. The other half of the intergenerational correlation can be attributed to cultural inheritance by a daughter from her mother in the form of role model effects, learning externalities and transfer of reputation and social capital.[10] In the case of sons, the lower bound estimate is *negative* and statistically insignificant which implies that the observed partial correlation may be driven entirely by the unobserved factors common to both generations. The results from the sensitivity analysis yield the same conclusions as above.[11]

A better understanding of occupational mobility in a developing economy is important for the design of appropriate poverty alleviation policies. Mobility from agriculture to non-

[9] The empirical methodology proposed by AET (2005, 2000) can be used to provide a lower bound on intergenerational occupational correlation under the assumption that the 'selection on observables' is at least as large as the 'selection on unobservables'. As we discuss in more detail later in the text, the assumption that the selection on observables dominates the selection on unobservables is a natural one for analyzing the role of cultural inheritance in intergenerational occupational mobility which is the focus of this paper. The univariate probit model assumes "no selection on unobservables" and thus can be thought of as the upper bound estimate of the intergenerational correlation.

[10] Note that the environmental factors like role model effects and learning externalities only affect the occupational choice of children and thus are NOT subsumed under the *common* intergenerational correlation.

[11] Following AET (2005, 2000) we also estimate the bias in the partial correlation estimates from univariate probit. The estimates of the bias might be useful as robustness check as they are not dependent on distributional assumptions. However, as noted by AET (2005, 2000), the bias estimates are based on the strong assumption that *the bias in the linear projection is similar to the bias in the probit equation.* Since this assumption is difficult to justify, we chose not to present the bias estimates (available upon request). We, however, note that the bias estimates also lend strong support to the central conclusions discussed above.

farm is often an avenue to escape poverty trap (WDR (2005); Lanjouw and Feder (2001)). In the presence of cultural inheritance effects, the standard cost-benefit analysis is likely to under-estimate the long-run social returns to policy interventions that encourage non-farm participation (like microcredit programs), as the intergenerational multiplier effect arising from factors like role model effects is ignored. Moreover, non-farm participation often leads to 'visible' income contribution by women and thus positively affects their bargaining power.[12]

The rest of the paper is organized as follows. Section 2 provides a conceptual framework that underpins the empirical work presented in the subsequent sections. The section 3 discusses the data and variables, while the next section presents some preliminary evidence. Section 4, arranged in a number of subsections, presents the main empirical results that focus on gauging the role played by unobserved common determinants of occupational choice across generations following the approach due to AET (2005, 2000). Section 5 concludes the paper with a summary of the main findings.

(2) The Conceptual Framework

In this section, we outline a simple model of participation in nonfarm sector highlighting different channels through which intergenerational linkages may operate. Our focus is on the role cultural inheritance might play through factors like role model effects, learning externalities and transfer of reputation and social capital from parents to children. The model is based on the standard occupational choice model but is augmented to capture the

[12] Women's work in agriculture is usually unpaid and remains invisible in a developing country like Nepal.

essentials of the intergenerational linkages.[13]

There are two sectors in the economy: agriculture (A) and non-farm sector (N). At the beginning of the working life, every person in the economy decides which sector to work for. Each individual is endowed with an innate ability $\theta_i \in [0, 1]$ that captures the attributes that are relevant for non-farm sector. So the higher is θ_i the better suited an individual is for non-farm employment. A fundamental source of intergenerational linkage arises from the fact that the genetic endowments of a child (θ_i) are likely to be correlated with those of parents. The innate ability parameter θ_i is not known with certainty and every individual has to form an estimate utilizing all the available information contained in an appropriately defined information set.

In addition to ability, every individual is endowed with a vector of initial capital stock k_i comprised of human, financial, physical, and social capital. The higher is the level of k_i the higher is the probability of success in non-farm activities. Parents can influence this initial capital stock k_i through their investment in a child's human capital (e.g. education) and their transfer of financial and physical capital. In addition, parental occupation can also influence their offsprings' human capital as children can gain valuable skills and experience by observing their parents at work, and by informal apprenticeship in parents' work place, especially when the nature of occupation is such that the workplace is in close proximity to home.[14] The parents, when successful in non-farm, often transfer significant reputation

[13]The model utilized here can be viewed as an extension of the celebrated contributions of Becker and Tome (1979 and 1986) and the recent extensions proposed in Sjogren (2000).

[14]As noted by Lentz and Laband (1983), this proximity of work place to home is an important factor behind the observed strong intergenerational following in occupations like agriculture. This proximity is also important in case of the household based activities common in the microcredit programs because of cultural inheritance.

capital and a rich social network (social capital) to their children.

At the beginning of the working life, individual i takes the endowment of capital and the estimate of ability $(k_i, \tilde{\theta}_i)$ as given, and optimally chooses the occupation $d_i \in \{A, N\}$. Let the information set available to individual i choosing occupation is denoted as Ω_i which include k_i and $\tilde{\theta}_i$. Let $F(Y_i \mid A; \Omega_i)$ denote the conditional distribution of income (Y_i) when individual chooses agriculture and the information set is Ω_i.The associated probability density function is denoted as $P(Y_i \mid A; \Omega_i)$. The preference of an individual i is represented by a concave utility function, $U_i(.)$, that reflects, among other things, the risk preference [15]

We define the expected utility from choosing agriculture as:

$$V_i(A, \Omega_i) \equiv \int U_i(Y_i) P(Y_i \mid A; \Omega_i) dY_i$$

Analogously the expected utility from choosing non-farm sector is:

$$V_i(N, \Omega_i) \equiv \int U_i(Y_i) P(Y_i \mid N; \Omega_i) dY_i$$

The individual chooses non-farm employment iff the following holds:[16]

$$V_i(N, \Omega_i) - V_i(A, \Omega_i) \geq 0 \tag{1}$$

[15]The preferences of a child are likely to be correlated with those of her parents. In addition, parents can also induce changes in children's preferences by acting as their role models (Durlauf, 2000). The intergenerational correlation in preferences implies, for example, that, on an average, the children of the parents more inclined to taking risk will themselves be risk takers, and thus are more likely to become non-farm entrepreneurs.

[16]Assuming that the tie is broken in favor of non-farm sector.

The probability that an arbitrary individual i drawn from the population will decide to work in the non-farm sector is $\Pr(V_i(N, \Omega_i) - V_i(A, \Omega_i) \geq 0)$. At the heart of the occupation selection process is the formation of expectation about payoffs from different options using the information set Ω_i. A critical element of the information set is the occupational choices of the parents as they reveal two types of relevant information: (i) information about ones own genetic endowment (or innate ability), (ii) information about the characteristics of a certain occupation. For example, if parents are successful (unsuccessful) non-farm entrepreneurs, the estimate of children's ability to be successful in similar occupation will be revised upward (downward). The parental success in non-farm may thus inspire the children to follow in their footstep due to "success bias" emphasized in the literature on cultural evolution (Boyd and Richerson, 1985, 2005, Henrich and McElreath, 2003). Another important channel is that revelation of information might reduce the uncertainty about the parental occupation, and thus induce risk-averse children to prefer the parental occupation to other alternatives. Thus, the information revealed by parental choices (and their outcomes) can influence children's occupation decision through their effects on the conditional distribution function of income Y_i giving rise to role model effects (Manski 1993; Streufert, 2000). For example, consider a child's participation decision in non-farm sector ($d_i = N$). The parental role model effects (more broadly cultural inheritance) imply that the conditional distribution of income when parents are in non-farm $F(Y_i \mid N;\, N^p, \Omega_i)$ is stochastically dominant over the conditional distribution of income with neither of the parents is in non-farm $F(Y_i \mid N;\, A^p, \Omega_i)$.[17]

[17]Note that given a concave utility function both first and second order stochastic dominance are sufficient.

The model presented above can also be used to explain intergenerational correlations running along gender lines. First, the genetic transmissions might have a gender dimension. For example, the preference of a daughter (son) is likely to be more aligned with that of her (his) mother (father) compared to that of her (his) father (mother). Second, and probably the most important factor behind gender effects in intergenerational linkages in occupational choices, is the gender dimension in cultural inheritance due to role model effects. The information revealed by the choices (and consequent outcomes) of an older member of a society will be more informative for the choices of a given younger member the closer he/she is to the younger person in an appropriately defined socioeconomic space. The individuals can be grouped together by partitioning the socioeconomic space according to different exogenous (like ethnicity, gender) or endogenous (like schooling) characteristics. The finer the partitioning the more informative is the information revealed by the choices of a member of a given group for the other members of that same group. It follows that, given the membership in a family, gender creates a finer partitioning, and the mother becomes the natural role model for the daughter, and the father for the son. This has also implications for learning by doing and observing as the daughter (son) 'sees' and 'hears' primarily what her (his) mother (father) does and says. Another potential channel for gender effects is that the effects of parental social capital might run predominantly along gender lines; the mother's social network might be more easily accessible to a daughter. Moreover, social norms regarding gender roles might also contribute to gender effects in occupation choice. The existence of gender effects for a daughter means that the conditional distribution of income from non-farm employment when mother is in non-farm $F(Y_i \mid N; N^m, \Omega_i)$ stochastically dominates the conditional distribution with father in non-farm $F(Y_i \mid N; N^f, \Omega_i)$. As emphasized before, the strength of the role model effects is likely to differ across genders depending on the gender norms regarding the social and economic interactions.

In a traditional patriarchal society like Nepal, we expect the cultural inheritance to be stronger for daughters because of gender norms. The mother plays a dominant role in a daughter's life due to a combination of the gender effects discussed above and limited social interactions. The women in Nepal face both explicit and implicit discriminations in almost all spheres of social and economic interactions (Bennett, 2005, ADB, 1999). The inheritance customs and practices are explicitly against women's ownership of productive resources like land.[18] There is clear gender division of work, women's economic activities are concentrated in and around the household, while men participate more in the formal labor market (Acharya and Bennett, 1983). The men also are more mobile geographically, and are likely to embark on short-term migration for work in the cities (in addition to the Nepalese cities, also the Indian cities closer to the Nepal border). The absence of the father from the household due to migration or participation in the formal labor market implies that the interaction between father and son may be less frequent which will tend to weaken the role model effect of the father on the son.[19] There is striking gender bias in favor boys in parental investment in human capital. For example, in 1996, the literacy

[18] Although 1990 constitution enshrines equal rights irrespective of gender, the family laws that govern property rights, inheritance, marriage and divorce reinforce the patriarchy and put severe constraints on women's command over resources. For example, the national Code of Nepal (Mulki Ain) of 1963 that codifies the inheritance system derives from the Hindu custom of patrilineal descent and a patrifocal residence system.

[19] This, however, does not mean that the total effect of a migrant father will be necessarily negative on the non-farm participation of the son. A migrant father may facilitate non-farm occupation by relaxing the credit constraint, for example.

rate for male was 57 percent and only 27 percent for female (ADB, 1999). The evidence from the data set used in this paper also confirms a striking gap in the years of schooling between the daughters and the sons (please, see appendix Table A.1). The fact that the girls are less likely to go to school or more likely to drop out early from school implies that their domain of interactions remains limited.

For the econometric estimation, we can now employ a standard probit model taking inequality (1) as the basis for our empirical specification. Specifically, we consider the binary response model (with slight abuse of notation):

$$N_i = 1\left\{N_i^* \equiv V_i(N, \Omega_i) - V_i(A, \Omega_i) \geq 0\right\}, \tag{2}$$

For estimation we impose linearity and assume that the latent variable N_i^* is generated from a model of the form

$$N_i^* = \alpha_p N_i^p + X_i' \gamma + \varepsilon_i \tag{3}$$

Where $X_i \subseteq \Omega_i$ is a vector of explanatory variables and ε_i is the idiosyncratic random disturbance term. In the econometric analysis, the vector of explanatory variables X_i is required to include regressors that can control for heterogeneity across individuals in terms of preferences (U_i), and the productivity, and pay-off information contained in Ω_i. Equation (2) forms the basis of much of our empirical analysis. A complete list of explanatory variables X_i is provided in appendix table A.1.

(3) The Data

The data for our analysis come from the Nepal Living Standard Survey (NLSS) 1995/96. The NLSS consists of a nationally representative sample of 274 primary sampling unit (PSUs) selected with probability proportionate to population size, covering 73 of the 75 districts in Nepal. In each of the PSUs, 12 households were also selected randomly (16 households in the Mountain regions) providing a total sample size of 3373 households. From these households, about 8394 individuals in the age group 14 to 70 years participated in the labor force. For these individuals, information from the survey can be used to identify the parents. Some of the fathers did not report their labor force participation, reducing the sample to 8048. Splitting the sample into male and female gives us a sample of 4025 males and 4023 females. The sample size is further reduced because many of the villages did not display any employment diversification. To avoid perfect fit due to lack of within village employment variation, regressions automatically dropped about 1632 observations in the case of female sample and 287 observations in the case of male sample. In addition, about 354 mothers in daughters' sample and 819 mothers in sons' sample did not report labor force participation. The results presented in the paper are based on the samples which dropped these observations. We conducted the same empirical analysis with out dropping these observations while introducing a dummy to indicate lack of information on mothers' employment status. The results are similar and are omitted for the sake of brevity.

The NLSS contains detail information on employment by sectors and by occupations at individual levels. The survey is unique in the sense that it contained an entire section of questionnaire on parental information, including level of education, sector of employment and place of birth. From the occupation information, we define our dependent variable as a binary variable taking the value of one if an individual is employed in nonfarm activities and zero otherwise.[20] Similarly we define separate indicator variables for mother and father showing their employment in nonfarm sector.

Table 1 reports the basic statistics on employment status of daughters and sons. The (unconditional) probability of being employed in nonfarm sector is estimated to be around 44 percent for a man and 16 percent for a woman. In our data set, average participation rates of father and mother are around 20 percent and 8 percent respectively. A comparison of sons and daughters' employment status conditional on father's and mother's employment status reveals that the probability of being employed in non-agriculture sector is markedly higher for both sons and daughters if father or mother were employed in non-agriculture as well. We also tested the significance of difference between probabilities of being employed in nonfarm sector by parent's employment status (farm vs nonfarm). The test results reported in Table 1 indicate that in all cases, the null hypothesis of no difference can be rejected with a P-value equal to 0.00. According to Table 1, mother's participation in non-farm sector appears to have a larger effect, compared with father's non-farm participation, on both sons' and daughters' probability of participation in non-farm sector. The intergenerational occupational linkage appears to be much stronger for daughters relative to sons.

(4) Preliminary Evidence

With some indication of positive intergenerational correlations between parents' and

[20]Non-farm is defined as non-agricultural, i.e., excludes SIC one digit code '0'. Non-farm thus includes industries and services.

children's occupational choices above, we turn to more formal regression analysis. Starting from a simple Probit regression of son's and daughter's occupations on parental occupations, we take a sequential approach in presenting the results, introducing an array of control variables in subsequent steps. The upper panel in Table 2 reports the regression results for daughters and lower panel for sons.

Column (1) in Table 2 reports the coefficients of N^f (father in non-farm) and N^m (mother in non-farm) in the regression for son's and daughter's participation in nonfarm sector. The results from the probit regression without any controls show that mother's non-farm participation has a significant positive influence on daughter's probability of participation in the same sector. The marginal effect of a mother's participation in nonfarm sector (N^m) is estimated to be 0.43 which is large compared to the daughter's average probability of participation in non-agriculture of 0.16. In contrast, father's participation in nonfarm (N^f) appears to have no statistically significant effect on daughter's likelihood of being employed in the same sector. The results for sons reported in the lower panel of Table 2 indicate significant positive correlation between father and son's employment in the nonfarm sector. The marginal effect of father's employment in nonfarm sector (N^f) is around 0.15 which is statistically significant at 1 percent significance level. Compared with father, mother's nonfarm participation (N^m) has a smaller marginal effect (0.10) which is significant at 5 percent level.

The next set of results reported in column (2) of Table 2 includes a large number of household and individual level characteristics as control variables. The access to non-farm jobs may depend on the personal networks that often run along ethnic group/caste (see, for example, Dreze, Lanjouw and Sharma, 1998). To capture the variations in access to non-farm jobs, we include a set of dummies depicting the ethnicity (caste and tribe) of the individual in the regression. We also include dummies showing if there is any short/long-term migrant in the household, as migration frequently occurs on the basis of personal networks. A set of household variables including household size and composition are also added to the set of control variables. As discussed in the conceptual framework, human and financial capital variables are important links in the intergenerational transmissions of socioeconomic status. In addition to the level of education, we include the age of an individual as a human capital variable representing the work experience.[21] The education levels of parents and spouse are also included as additional human capital controls. The inherited land (as the most important form of collateral), remittances received, and travel time to the nearest commercial bank are included as controls for access to capital[22]. We include an individual's marital status to account for taste and/or life-cycle related heterogeneity. The summary statistics for these explanatory variables are presented in appendix Table A.1. A comparison of daughters' and sons' samples in Table A.1 shows that the difference in the means of individual and family characteristics across parental occupation is much more pronounced in case of sons sample. This indicates that selection might be relatively more important for the sons' sample.[23]

The results reported in column (2) in Table (2) show that the added set of regressors are powerful determinants of nonfarm participation decision. With the inclusion of these

[21]In addition, age and its squared term capture any cohort effect.

[22]The ethnicity dummy may also capture access to credit.

[23]This implies that in our case the girls' sample is more like the preferred C8 (catholic school 8th graders) sample in AET (2005).

controls, the Pseudo R^2 increases from 0.10 to 0.52 in daughter's sample and from 0.03 to 0.23 in son's sample. However, the addition of the powerful set of controls does not affect the estimated intergenerational partial correlations in any significant way. The marginal effect of N^m (mother in non-farm) is estimated to be 0.41 which is virtually identical to the estimate from the regression with no controls (0.43). It is still highly statistically significant ($t = 8.04$). In the sons sample, the marginal effect of father's employment in nonfarm sector (N^f) is estimated to be 0.16 which is also nearly identical to our earlier estimate from regression with no controls (0.15).

Although the regressions in column (2) include a large set of individual and household level controls, the intergenerational correlation in occupation may still result, *spuriously*, from the fact that parents and children may face similar labor market opportunities. For instance, if both parents and children live in an area with better non-farm opportunities (say location of a textile mill), then intergenerational correlation in non-farm participation may be an artefact of not adequately controlling for non-farm opportunities in the regression. To control for unobserved location specific heterogeneity in non-farm opportunities, we included village level fixed effects in the estimation (151 and 241 village dummies in daughter's and son's regressions respectively). The village fixed effects may also capture other village specific determinants of occupational choice like peer effects and agglomeration forces. In addition, we define the share of non-farm employment in total employment of an individual's age cohort in her district of birth as an additional control for labor market opportunity and possible peer effects. This may capture the time varying part of labor market opportunities in a village.

The results from regressions with village fixed effects are reported in column (3) of Table 2. The addition of village level fixed effects as well as a measure of intertemporal labor market opportunity leads to an increase in the explanatory power of the regressions further. The Pseudo R^2 of the regression is 0.62 in daughter's sample and 0.53 in son's sample. Despite the inclusion of such a large number of controls (village plus household plus individual level controls), the qualitative results regarding intergenerational occupational correlations remain largely unchanged. Although the marginal effect of N^m (mother in non-farm) on a daughter's nonfarm participation declines, it is still large (0.30) and is statistically highly significant with a t-value=6.33. The marginal effect of N^f (father in non-farm) on a son's nonfarm participation is now 0.10 and is statistically significant at 1 percent level. Consistent with the available evidence in the literature on income mobility (see, for example, Solon, 2002), the evidence also indicates that the cross gender effects are not important as they are not statistically significant in column (3) of Table 2.

(5) Genetic Transmissions and Cultural Inheritance

The results discussed so far show that the intergenerational occupational correlations between parents and children run along gender lines (father-son and mother-daughter). The evidence indicates that the estimated partial correlations are not solely due to the 'tangible' determinants of occupational choice like education, assets, and ethnicity as they are already controlled for in the regression. The results can not be driven by village level factors like peer effects and geographic agglomeration as we include village fixed effect. However, as discussed before, an important question from the policy perspective is how much of the partial correlations uncovered in column 3 of table 2 is causal due to environmental factors related to cultural inheritance like role model effects and learning externalities as opposed to pure genetic correlations in occupational choice.

In the absence of credible identifying instruments, we utilize a number of ways to ascertain whether the observed intergenerational correlations can be explained solely in terms of unobserved ability correlations (and other unobserved common determinants). They include (*i*) sensitivity analysis a la Rosenbaum and Rubin (1983), Rosenbaum(1995) and AET (2005, 2000); (*ii*) estimation of lower bounds on the role played by cultural inheritance in the intergenerational correlations using the technique developed by AET (2005, 2000).

(5.1) Sensitivity Analysis

The regression results presented in the previous section demonstrate that the inclusion of a large and powerful set of controls does not lead to a substantial weakening of intergenerational occupational correlations especially for the daughter. This suggests that the selection on observables is dominant and a relatively small amount of selection is due to unobservables. We now explore the question whether a small amount of selection on unobservables can explain away the estimated partial correlations in intergenerational occupational choices in table 2.

Consider the following bivariate probit model for individual i.

$$N_i = 1(\alpha_p N_i^p + X_i'\gamma_1 + \delta_j \omega_j + \xi > 0), \tag{4}$$

$$N_i^p = 1(X_i'\beta_1 + \delta_j \omega_j + u > 0) \tag{5}$$

$$\begin{bmatrix} u \\ \xi \end{bmatrix} \sim N \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix} \tag{6}$$

where N_i (also N_i^p) is a binary occupation choice variable which takes the value 1 for non-farm and zero otherwise, ω_j is the village dummy (fixed effect) included to control for unobserved and observed community level determinants including labor market opportunities and peer effects. We estimate the magnitudes of intergenerational correlations for different values of the correlation (ρ) between the unobserved determinants of nonfarm participation of parents (u) and children (ξ).[24] The vector of explanatory variables (X) is the same as that in the regression results presented in column (3) of Table 2. However, the inclusion of village level fixed effect in the regression describing parental participation in nonfarm sector (N^p) causes problem in estimation as there are cases of perfect fit due to the absence of parental occupational diversification in a village (all 0s or 1s for the occupation dummy). When we exclude such cases, the sample size reduces to 1126 in daughter's sample and 2547 in son's sample. The results for these restricted samples are reported in columns 2 and 4 of Table 3 for daughters and sons respectively. An alterna-

[24] As discussed in AET (2005, 2000) the bivariate probit model above is identified because of nonlinearity. However, such identification based on functional form alone in the absence of valid instruments is treated with skepticism in applied literature (termed "weak identification"). In what follows, the bivariate probit model is treated as underidentified and thus the sensitivity analysis is performed across alternative values of ρ.

tive approach that keeps the sample size same as in Table 2 relies on an index of village fixed effects estimated from the simple probit regressions reported in column 3 of Table 2. The results for these unrestricted samples are presented in columns 1 and 3 of Table 3 for daughter's and sons respectively. Following AET (2005), the sensitivity analysis is performed for $\rho = 0.1, 0.2, 0.3, 0.4, 0.5$. Note that the correlation coefficient ρ represents only that part of genetic correlation across generations which influence the occupational choice.

For daughters, the results from the unrestricted sample show that the marginal effect of the mother's employment in nonfarm sector declines to 0.22 when ρ =0.10, and to 0.15 when ρ =0.20. The estimated marginal effect continues to decline with an increase in ρ but is still positive though small in magnitude when ρ is as high as 0.50. Interestingly, all the values of marginal effect are also statistically significant at 5 percent or less except for the case when ρ =0.50. The conclusions derived from the restricted sample reported in column 2 are similar to that of the unrestricted sample; the marginal effects are, however, in general, larger in magnitude. These results suggest that barring sampling error, the unobserved genetic correlations pertinent to occupation choice would have to be greater than 0.50 to explain away the entire effect of N^m (mother in nonfarm) on a daughter's nonfarm participation.

In the case of sons, the marginal effect of father's nonfarm participation becomes numerically small (0.05) and statistically insignificant in the unrestricted sample when $\rho = 0.10$. For values of ρ equal to or greater than 0.2, the marginal effect becomes *negative*. The results are again very similar in the case of the restricted sample. These results suggest that the estimated effect of N^f (father in nonfarm) on son's nonfarm participation may be entirely driven by common unobserved factors like genetic transmissions. As discussed before this difference in the intergenerational occupational persistence across gender is consistent with a model of cultural inheritance in a traditional patrilineal society where the domain of social and economic interactions for women is restricted in and around the household and also they have very little educational attainment or geographic mobility.

(5.2) Lower Bounds on the Effects of Cultural Inheritance

The sensitivity analysis above indicates that the value of ρ would have to be larger than 0.50 to completely explain the effect of mother's nonfarm employment on that of daughters found in Table 2. This can be interpreted as strong evidence in favor of a causal role of cultural inheritance from mother to daughter in occupation choice. But there is no estimate of ρ in the literature which we can use as a benchmark. The available evidence from Behavioral Genetics shows that both the genetic transmissions and environmental factors are important in the correlation between the parents and children, especially for complex traits and behavior.[25] The problems in pinning down a plausible range for ρ are more daunting in our case as other explanatory variables like education (both children's and parents'), ethnicity (i.e., caste and tribe), and assets are likely to pick up a substantial part of this correlation.[26] In the absence of any plausible way of judging the magnitude of the genetic correlations relevant for occupation choices in a rural economy as captured by

[25]For example, the correlation between IQ scores of parents and children is around 0.5 (Plomin et. al., 2001, Griffiths et. al. 1999). This correlation includes both the effects of nature (heritability) and nurture (familiality).

[26]This implies that the value of ρ relevant for our analysis should be smaller than otherwise.

ρ, we utilize an approach suggested by AET (2005). This allows us to estimate both the magnitude of ρ and bounds for the intergenerational correlations.

To illustrate the basic insights behind AET (2005) approach, we consider equation (3) (with village fixed effects added). It defines the latent variable N_i^* that determines children's participation in nonfarm sector as:

$$N_i^* = \alpha_p N_i^p + X_i' \gamma_1 + \delta_j \omega_j + \varepsilon \tag{7}$$

where N_i^p is the dummy variable for nonfarm participation by parents and ω_j is the village fixed effect for village j where individual i lives in. Let N^{p*} is the latent variable such that $N^p = 1$ if $N^{p*} > 0$ and zero otherwise. We can define the linear projection of N^{p*} on $X'\gamma, \omega$ and ε as (for notational simplicity the subscript is dropped) :

$$\text{Proj } (N^{p*} | X' \gamma_1, \omega, \varepsilon) = \phi_0 + \phi_{X'\gamma_1} X' \gamma_1 + \omega^{'} \delta + \phi_\varepsilon \varepsilon \tag{8}$$

Following AET (2005), we can interpret $\phi_{X'\gamma_1}$ as the "selection on observables" and ϕ_ε the "selection on unobservable". However, unlike AET (2005), we use a village level fixed effect to sweep off the observed and unobserved village level determinants. This implies that the selection on observables ($\phi_{X'\gamma_1}$) and unobservables (ϕ_ε) both represent only the individual characteristics. An advantage of this formulation is that it fits well with the notion that the 'unobservables' are like 'observables'. An alternative approach is to include the village fixed effects as part of the observables. The argument is that the location of an individual is an observable characteristic.[27] The linear projection of N^{p^*} in this case becomes:

$$\text{Proj } (N^{p*}|Z'\gamma_2, \varepsilon) = \phi_0 + \phi_{Z'\gamma_2} Z'\gamma_2 + \phi_\varepsilon \varepsilon \quad ; Z = (X, \omega) \text{ and } \gamma_2 = (\gamma_1, \delta) \tag{9}$$

The advantage of this formulation is that it is more likely to satisfy the condition that selection on observables is dominant which helps in deriving the lower bound on intergenerational occupational linkage (see below).[28] We perform the analysis under these alternative interpretations (equations (8) and (9)).[29] Note that in the case of univariate probit regressions, the maintained assumption is that there is no selection on unobservable, i. e, $\phi_\varepsilon = 0$.

AET (2005, 2000) and Altonji, Conley, Elder, and Taber (2005) (henceforth ACET (2005)) show that selection on observables can be used as a guide to selection on unobservables. They point out that in many applied economic applications, it is a natural assumption that the selection on observables dominates the selection on unobservables which leads to the following conditions in our case (analogous to condition (3) in AET (2005)):

$$\phi_{X'\gamma_1} \geq \phi_\varepsilon \geq 0 \tag{10}$$

$$\phi_{Z'\gamma_2} \geq \phi_\varepsilon \geq 0 \tag{11}$$

[27]We thank Chris Taber for pointing out the alternative interpretations of the fixed effects.

[28]Since location choice is endogeneous, the village fixed effects will capture some of the unobserved individual characteristics which are common to the villagers.

[29] A third alternative is to exclude the fixed effects altogether and use village level observed controls (share of non-farm). The conclusions of this paper remain unchanged in this formulation, although the lower bound estimates are larger than reported here.

Following AET (2005), we can implement the econometric estimation under the above restriction(s) and treat the estimate of α_p (equation (7)) corresponding to the case of equality of selection on observables and unobservables (i.e., for example, $\phi_{X'\gamma_1} = \phi_{\varepsilon}$) as the lower bound on the part of intergenerational occupational linkage that is not driven by genetic transmissions and can be attributed to factors like role model effect and learning externalities. The inequality conditions (10) and (11) above are eminently plausible in our case due to the following considerations.[30] First, as pointed out earlier, the addition of a set of rich and powerful determinants of occupation choice affects the strength of intergenerational linkages only marginally although the Pseudo R^2 goes up dramatically. For example, in daughter's sample, the Pseudo R^2 increases from 0.10 to 0.52 when we include a rich set of determinants of occupational choice including education levels of children, parents and spouse, inherited land, and ethnicity. The estimated partial correlation in non-farm participation by mother and daughter is, however, barely affected (it declines from 0.43 to 0.41). This indicates that (i) the observables explain a large part of the variations in non-farm participation, and thus leave room for only a limited role for the unobserved individual characteristics; (ii) the estimated partial correlation is robust to possible inclusion of additional controls (if such data were available). Second, the data for our analysis come from a multipurpose household survey which was conducted primarily for poverty assessment. Since the role of non-farm occupations as an avenue to escape poverty traps in a low income agrarian economy is much discussed (Lanjouw and Feder, 2001), it is only natural that the survey includes rich information on the determinants of non-farm participation identified

[30]We are grateful to Chris Taber and Todd Elder for clarifying the relevance of the conditions (10) and (11) in our analysis.

in the recent literature. This means that these observable characteristics are likely to pick up a substantial part of the unobserved genetic correlations relevant for occupation choice, a point mentioned earlier, but worth emphasizing again here. This also means that the selection on unobservable genetic endowment captured in ϕ_ε will be much smaller in our analysis. Third, we can decompose the error term in the occupation choice by children as in equation (4): $\xi = \xi_1 + \xi_2$ where ξ_1 is the part of selection on unobservables that is common to both generations but is determined at the time of parental occupation choice, and ξ_2 represents the unobserved shocks that occur during the children's occupation choice. As shown by AET (2005), this implies that selection on observables is greater providing additional justifications for inequality conditions (10) and (11) above.

In the case of bivariate probit (equations 4-6), the lower bound estimate of α_p can be estimated by imposing the following conditions depending on the treatment of fixed effect:

$$\rho = \frac{Cov(Z'\beta_2, Z'\gamma_2)}{Var(Z'\gamma_2)} \; ; \; \beta_2 = (\beta_1, \delta) \tag{12}$$

$$\rho = \frac{Cov(X'\beta_1, X'\gamma_1)}{Var(X'\gamma_1)} \tag{13}$$

Table 4 reports the estimates of the lower bounds on the intergenerational partial correlation (i.e., lower bound estimates of α_m and α_f) that can be attributed to cultural inheritance from parents by the children. The inclusion of village dummies leads to computational difficulties and convergence problems in the estimation of the bivariate probit model. The results discussed earlier in Table 3 show that the index of village fixed effects estimated from univariate probit model performs equally well as village level dummies in controlling for spatial labor market opportunities and possible peer and agglomeration effects. To avoid the non-convergence problems, we use this index in the regressions reported in Table 4. The first panel reports the results from bivariate probit model under the constraint defined in equation (12) and the third panel shows the corresponding results under equation (13). The central conclusions of this paper are, however, not sensitive to the treatment of fixed effects and we focus our discussion on the case defined by equation (12) for the sake brevity. The estimated magnitudes of correlations between unobserved determinants of parent and children's nonfarm participation are similar: 0.21 for daughters and 0.25 for sons. The estimates show that the intergenerational correlation between mother's and daughter's nonfarm participation is highly statistically significant (t-value=4.81). The estimated coefficient α_m is positive and large in magnitude (0.685) with a marginal effect of 0.146. In contrast, for sons, the estimated $\alpha_f = -0.143$ with a t-value of 1.74. The results in panel 1 of Table 4 thus strengthen our central conclusion from the sensitivity analysis in section (4.1) above that the estimated partial correlation in the nonfarm participation of mother and daughter is not likely to be driven entirely by the genetic correlations; at least part of the occupational linkage seems causal reflecting cultural inheritance through role model effects, learning externalities and transfer of reputation and social capital from mother to the daughter as discussed in the conceptual framework above. In contrast, the lower bound estimate for the correlation in father's and son's nonfarm participation is negative implying that the observed (positive) intergenerational correlation may be an artefact of genetic transmissions across generations.[31]

[31] We caution here that the fact that the lower bound estimate is negative for the father and son should not be taken as conclusive evidence for an absence of intergenerational linkage. As mentioned before the lower

To ensure robustness of our findings, we also check whether these results are driven by the joint normality assumption underlying the bivariate probit model. Following AET (2005), we utilize the following semi-parametric specification for the error terms:

$$
\begin{aligned}
u &= \theta + u^* \\
\xi &= \theta + \xi^*
\end{aligned}
$$

Where u^* and ξ^* are independent standard normals and θ is unrestricted. Bivariate probit model estimated earlier is thus a special case where θ is assumed to be distributed as normal. We estimated the model using nonparametric maximum likelihood method suggested by Heckman and Singer (1984) and AET (2005). The estimation method treats the distribution of θ as discrete; in practice, we obtain two points of support for θ. The estimated ρ and α_p are reported in the second and fourth panels of Table 4. Again, for the sake of brevity, we focus on the case when the village fixed effects are treated as part of the observables index (second panel in Table 4). The estimated magnitudes of ρ are smaller compared with those from the bivariate probit model, but as before they are similar for sons (0.178) and daughters (0.163). However, the overall results regarding the intergenerational effects remain unchanged. The effect of N^m (mother in nonfarm) on daughter's nonfarm participation is statistically highly significant, and positive ($\alpha_m = 0.665$). The implied marginal effect is 0.135 which is virtually identical to that found in the bivariate

bound estimates are likely to underestimate the strength of occupational linkage given that the selection on observables is likely to dominate. This also implies that the evidence from the bounds estimates in favor of a causal effect of mother's non-farm participation arising from cultural inheritance is very strong.

probit model (0.146). For sons, the estimated lower bound on intergenerational correlation is positive but much smaller in magnitude (marginal effect=0.086) and statistically insignificant.

(6) Conclusions:

The economic literature on intergenerational mobility has witnessed a renewed interest in recent years. However, most of the existing economic research focuses on the income correlations between father and son(s) in the context of developed countries. Also, the possible role played by cultural inheritance has received relatively less attention in economic literature on intergenerationl mobility. Using data from a developing country, Nepal, we present evidence on the intergenerational occupational mobility from agriculture to non-farm sector with an emphasis on the gender differences in cultural inheritance arising from gender norms regarding social and economic interactions. Since it is extremely difficult, if not impossible, to find credible instrument(s) to address the genetic correlations (ability and preference), we employ the recent econometric approach developed by Altonji, Elder and Taber (2005, 2000) to ascertain if the estimated partial correlations in non-farm participation can be attributed solely to genetic transmissions or at least part of the effect is likely to be causal due to factors like role model effects (more broadly cultural inheritance). The approach uses the degree of selection on observables as a guide to the degree of selection on unobservables. It allows us to estimate lower bounds on the part of the intergenerational occupational correlations that can be attributed to intergenerational cultural inheritance due to factors like role model effects, informal apprenticeship, learning externalities, and transfer of reputation and social capital. The results show that the observed partial correlation between the father and a son can be easily explained away by a moderate correlation in genetic endowments across generations. In contrast, for the mother and daughter(s), the intergenerational occupational linkage is very strong, and it is unlikely that the estimated partial correlation is driven solely by the unobserved genetic correlations. The evidence points to a causal effect of mother's occupation choice on that of the daughter beyond the widely discussed channels like human capital, assets and ethnicity. The estimated lower bound on the effects of cultural inheritance for mother-daughter intergenerational occupational correlation shows a marginal effect of 0.14. The gender differences in the role of cultural inheritance in intergenerational occupational persistence indicate that the social norms like gender based division of labor and restrictions on geographic and educational mobility can make it extremely difficult for women to move out of traditional economic activities like agriculture. This provides a link in the analysis of poverty trap in developing countries, and brings into focus the intergenerational occupational linkage as an important factor in understanding the gender bias in economic mobility against women in developing countries.

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Table 1: Nonfarm participation of children conditional on Parent's Employment Status (weighted mean)

	Probability of being Employed in Nonfarm Activities	
	Daughters	Sons
Mother's employment in		
Farm	0.13	0.43
Nonfarm	0.54	0.63
Difference	0.414***	0.20***
Father's employment in		
Farm	0.14	0.41
Nonfarm	0.24	0.57
Difference	0.10***	0.16***
Unconditional	0.16	0.44

* significant at 1%; ** significant at 5%; *** significant at 1%

Table 2: Probit Estimates of Intergenerational Correlations

	(1)	(2)	(3)
	Daughter's sample		
Father in Non-Farm (n^f)	-0.072	-0.062	-0.068
	[0.016]	[0.012]	[0.009]
	(0.65)	(0.49)	(0.46)
Mother in Non-farm (n^m)	1.286	1.283	1.157
	[0.433]	[0.406]	[0.299]
	(8.21)**	(8.04)**	(6.33)**
Pseudo-R^2	0.1	0.522	0.622
	Son's Sample		
Father in Non-Farm (n^f)	0.372	0.402	0.260
	[0.146]	[0.157]	[0.099]
	(4.92)**	(4.85)**	(2.79)**
Mother in Non-farm (n^m)	0.258	0.252	0.203
	[0.102]	[0.099]	[0.078]
	(2.16)*	(2.00)*	(1.38)
Pseudo-R^{2a}	0.035	0.227	0.527
Individual and household characteristics[b]	No	Yes	Yes
Village fixed effect	No	No	Yes

Note.- Entries are probit coefficients. Standard errors are corrected for intra-cluster correlations due to clustered sampling. t-values are in parentheses and marginal effect of each variable (evaluated at sample means) is shown in bracket.

a. Pseudo R^2 is defined as $Var(X'\gamma)/[1+Var(X'\gamma)]$

b. Regressors in coulmn 2 include level of education, age, age squared, dummy for married, household size & composition, inherited land, distance to bank, un-earned income, dummy for migrant member in the household, 3 ethnicity dummies, father, mother and spouse's education level. Regressors in column (3), in addition to above regressors, include share of nonfarm employment by age cohort, and an index of village fixed effect.

* significant at 5%; ** significant at 1%

Table 3: Estimates of Intergenerational Correlations for different values of correlation of disturbances in bivariate probit models

Correlation of Disturbances	Daughter's Sample: Mother in Non-farm (n^m) Unrestricted Sample[a]	Daughter's Sample: Mother in Non-farm (n^m) Restricted Sample[b]	Son's Sample: Father in Non-Farm (n^f) Unrestricted Sample[a]	Son's Sample: Father in Non-Farm (n^f) Restricted Sample[b]
ρ=0	1.116	1.260	0.304	.323
	[0.284]	[0.353]	[0.117]	[0.126]
	(7.68)**	(8.02)**	(3.60)**	(3.66)**
ρ=0.1	0.917	1.075	0.130	0.151
	[0.216]	[0.288]	[0.049]	[0.058]
	(6.35)**	(6.88)**	(1.54)	(1.72)
ρ=0.2	0.715	0.886	-0.046	-0.023
	[0.154]	[0.225]	[-0.017]	[-0.009]
	(5.00)**	(5.73)**	(0.55)	(0.26)
ρ=0.3	0.509	0.692	-0.222	-0.198
	[0.100]	[0.165]	[-0.082]	[-0.075]
	(3.63)**	(4.56)**	(2.72)**	(2.32)*
ρ=0.4	0.299	0.492	-0.400	-0.374
	[0.053]	[0.11]	[-0.143]	[-0.139]
	(2.19)*	(3.33)**	(5.02)**	(4.49)**
ρ=0.5	0.085	0.286	-0.578	-0.551
	[0.013]	[0.06]	[-0.201]	[-0.20]
	(0.64)	(2.00)*	(7.50)**	(6.84)**
N	2037	1126	2919	2547

Note.- Entries are probit coefficients. Standard errors are corrected for intra-cluster correlations due to clustered sampling. t-values are in parentheses and marginal effect of each variable (evaluated at sample means) is shown in bracket.

a.Regressors include level of education, age, age squared, dummy for married, household size & composition, inherited land, distance to bank, un-earned income, dummy for migrant member in the household, 3 ethnicity dummies, father, mother and spouse's education level, share of nonfarm employment by age cohort, and an index of village fixed effect.

b.Regressors include level of education, age, age squared, dummy for married, household size & composition, inherited land, distance to bank, un-earned income, dummy for migrant member in the household, 3 ethnicity dummies, father, mother and spouse's education level, share of nonfarm employment by age cohort, and an index of village level dummies.

* significant at 5%; ** significant at 1%

Table 4: Estimates of Lower Bounds for the Intergenerational Correlations

	Daughter's Sample		Son's Sample	
	ρ	α_m	ρ	α_f
	Bivariate Probit Estimation			
ρ=Cov($Z\gamma_2$, $Z\beta_2$)/Var($Z\gamma_2$)	0.214	0.685	0.255	-0.143
	(1.70)	[0.146]	(6.71)**	[0.053]
		(4.81)**		(1.74)
	Nonparametric Maximum Likelihood Estimation			
ρ=Cov($Z\gamma_2$, $Z\beta_2$)/Var($Z\gamma_2$)	0.163	0.665	0.178	0.086
	(0.24)	[0.135]	(8.09)**	[0.03]
		(3.50)**		(0.04)
	Bivariate Probit Estimation			
ρ=Cov($X\gamma_1$, $X\beta_1$)/Var($X\gamma_1$)	0.219	0.677	0.257	-0.146
	(1.43)	[0.144]	(4.59)**	[0.054]
		(4.75)**		(1.77)
	Nonparametric Maximum Likelihood Estimation			
ρ=Cov($X\gamma_1$, $X\beta_1$)/Var($X\gamma_1$)	0.177	0.665	0.156	0.086
	(0.20)	[0.135]	(7.80)**	[0.03]
		(3.50)**		(0.04)

Note.- Entries are probit coefficients. Standard errors are corrected for intra-cluster correlations due to clustered sampling. t-values are in parentheses and marginal effect of each variable (evaluated at sample means) is shown in bracket.
Regressors include level of education, age, age squared, dummy for married, household size & composition, inherited land, distance to bank, un-earned income, dummy for migrant member in the household, 3 ethnicity dummies, father, mother and spouse's education level, share of nonfarm employment by age cohort, and an index of village fixed effect.
* significant at 5%; ** significant at 1%

Table A.1: Summary Statistics by parental employment status.

	Daughter's Sample			Son's Sample		
	Mother's employment in			Father's employment in		
	Farm (N=1880)	Non-farm (N=157)	Difference	Farm (N=2309)	Non-farm (N=610)	Difference
Participation in Nonfarm employment (proportion)	0.13	0.54	0.414***	0.39	0.54	0.15***
Level of Education (Years)	1.63	2.66	1.03**	3.76	5.7	1.94***
Father's level of education (years)	1.15	2.01	0.96*	0.81	2.39	1.58***
Mother's level of education (years)	0.1	0.3	0.2	0.05	0.15	0.09*
Spouse' level of education (years)	2.07	2.05	-0.03	0.334	0.31	-0.024
Age	32.72	30.67	-2.05	37.13	28.88	-8.25***
Age squared	1230	1153	-77	1591	1020	-571***
Married	0.83	0.63	-0.19***	0.8	0.63	-0.17***
Household size(log)	2.01	2	-0.001	1.77	1.85	0.08***
Share of adult female	0.25	0.26	0.012	0.23	0.22	-0.01
Share of children	0.17	0.17	0.0001	0.15	0.14	-0.01
Share of Young	0.35	0.35	0.006	0.34	0.38	0.04***
Share of Old	0.03	0.02	-0.01	0.02	0.02	0.004
Inherited land (value in million Rs.) (log)	9.26	6.65	-2.61***	8.39	7.47	-0.92***
Travel time to nearest bank	2.65	1.78	-0.87***	2.91	2.34	-0.57***
Un-earned income (million Rs)	0.008	0.007	-0.001	0.005	0.005	0.0008
Migrant in the household	0.39	0.48	0.09	0.32	0.46	0.14***
Upper caste Hindu (Proportion)	0.36	0.21	-0.15**	0.36	0.28	-0.08***
Lowr caste Hindu (Proportion)	0.07	0.19	0.12*	0.07	0.15	0.08***
Tribal (Proportion)	0.29	0.23	-0.06	0.26	0.26	-0.006
Share of nonfarm in district by age cohort	0.14	0.2	0.06***	0.28	0.3	0.02***

* significant at 1%; ** significant at 5%; *** significant at 1%

Appendix Table A.2: Probit Estimation of Intergenerational correlations

	Employment Status	
	Daughter in Non-Farm Sector	Son in Non-Farm Sector
Mother in Non-farm Emplyoment	1.283	0.252
	(8.04)**	(2.00)*
Father in Non-farm Employment	-0.062	0.402
	(0.49)	(4.85)**
Level of education (year)	0.070	0.028
	(5.05)**	(3.80)**
Age	0.055	0.107
	(2.29)*	(7.16)**
Age Squared	-0.001	-0.001
	(1.85)	(7.28)**
Married (Yes=1)	-0.075	0.375
	(0.56)	(4.10)**
Household Size (log)	-0.293	-0.291
	(3.26)**	(3.70)**
Share of Adult Female	-0.150	-0.385
	(0.28)	(0.96)
Share of Children	0.337	0.385
	(0.84)	(1.22)
Share of Youth	0.452	-0.193
	(1.21)	(0.76)
Share of Old	0.118	-0.423
	(0.20)	(0.81)
Inherited Land (log)	-0.048	-0.008
	(5.84)**	(1.28)
Father's education (year)	-0.026	0.0003
	(1.56)	(0.03)
Mother's Education (year)	0.034	0.098
	(0.97)	(2.18)*
Spouse's education(year)	0.031	0.017
	(2.92)**	(0.92)
Travel time to Bank	0.007	0.008
	(0.63)	(1.04)
Unearned income	-12.758	0.038
	(3.29)**	(0.12)
Migrant in the household (yes=1)	-0.005	0.504
	(0.06)	(8.25)**
Upper Caste Hindu (yes=1)	0.089	-0.322
	(0.81)	(4.46)**
Lower Caste Hindu (yes=1)	0.100	0.227
	(0.67)	(2.00)*
Belongs to tribe (yes=1)	0.290	-0.170
	(2.63)**	(2.11)*
Constant	-1.581	-1.887
	(3.25)**	(5.41)**
Observations	2037	2919

Note.- Entries are probit coefficients. Standard errors are corrected for intra-cluster correlations due to clustered sampling. t-values are in parentheses.
* significant at 5%; ** significant at 1%