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ABSTRACT

Education and Household Welfare*

Using census data from Nepal we examine how the partial derivatives of predicted household welfare vary with parental education. We focus on fertility, child survival, schooling, and child labor. Female education is not as strongly associated with beneficial outcomes as is often assumed. Male education often matters more, and part of the association between female education and welfare is driven by marriage market matching with more educated men. Controlling for the average education of parental cohorts does not change this finding. But when we use educational rank to proxy for unobserved ability and family background, the positive association between female education and beneficial outcomes becomes weaker or is reversed. For women the association between educational rank and outcomes is strong: women who obtain more schooling than their peers in school have fewer children and educate them better. In contrast, for men the statistical association between education and household welfare remains strong even after we control for educational rank within their birth cohort.

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Keywords: child welfare, marriage market, Nepal, parental education and south Asia

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1. Introduction

A strong empirical association between mother's education and child welfare has been documented in numerous countries (see Behrman 1997 and 2010 for surveys). Educated mothers tend to have fewer children, and to have children who are healthier and better educated.[1] This relationship has received much attention in policy circles, and has led many to advocate an expansion of female education as a way to reduce fertility, improve human capital and, ultimately, foster long-term growth (e.g., Mason and King, 2001; World Bank, 2012a and 2012b). Given how far reaching these claims are, not only for economic development but also for demography and family welfare, they have attracted considerable scrutiny and there is a large economic literature devoted to this issue (for surveys, see Strauss and Thomas 1995, Orazem and King 2008, and Behrman 2010).

There are many well known reasons why observing a correlation between female education and child welfare is insufficient to infer a causal relationship from one to the other. In recent years many researchers have sought to overcome this difficulty by relying on experimental and quasi-experimental evidence at the individual or local level (Curie and Moretti 2003, Black et. al 2005, Plug 2004). While useful to test the reduced-form impact of specific interventions, experimental methodologies are ill-equipped to disentangle multiple causal channels, especially when they involve general equilibrium effects in multiple markets.

This paper seeks to cast some light on the multiple channels through which parental education influence fertility and child welfare. Using a large observational dataset, we decompose the correlation between parental education and child welfare into different components. While the approach does not allow the kind of causal inference that an experimental approach makes possible, it nevertheless opens an informative window on the relationship of interest. The approach should be seen not as a substitute for experimental approaches but rather as a useful complement.

We consider four indices of household and child welfare: (1) mother fertility; (2) child survival rate (an indicator of child health); (3) child schooling; and (4) child work. The focus of analysis is on the partial derivative of predicted fertility and child welfare with respect to parental education, controlling for

[1] A recent example is Andrabi, Das and Khwaja (2009) who show that, in Pakistan, children with a better educated mother get more help with homework and obtain higher test scores.

district fixed effects, parental age, and ethno-caste dummies. The reason we focus on partial derivatives is that they can be compared to the marginal treatment effects that guide policy and on which the current development literature focuses.[2] Although our partial derivatives cannot be given a causal interpretation in the way treatment effects can, presenting them in the same manner facilitates interpretation.

We first examine whether the partial derivative with respect to parental education is the same for father and mother education, and whether it varies with the level of education – e.g., whether an additional year of primary education predicts the same change in fertility or child welfare as an additional year of college education. We find large differences across gender and across schooling levels. The higher the education level of a mother, the fewer children she is predicted to have. In contrast, an additional year of schooling raises the predicted number of children among fathers with a low education, but reduces it among fathers with secondary education and above. Couples in which the husband has more than primary education are also predicted to be less likely to have a child in the year preceding the census.

Among low education mothers, an additional year of education increases the predicted survival rate of her offspring; the relationship tapers off slightly at higher levels of education. In contrast, father education is associated with a strong increase in child survival rate, but only for education levels above primary school. Parental education is also associated with higher school attendance and education attainment. The partial derivative is larger for father than mother education, and it tapers off at high levels of parental education, especially for mothers. A similar pattern is present for child work: an additional year of parental schooling is strongly associated with a reduction in predicted child work; the partial derivative is larger (twice as large) for father than mother education; and the relationship tapers off at high levels of parental education.

Next we examine how much of the predictive power of parental education is driven by the matching of spouses in the marriage market. If educated women make better mothers, they should on average be matched with someone whose reproductive success is also predictably higher, such as a better educated man. It follows that any positive relationship between mother's education and household outcomes would be reinforced by marriage market outcomes. This point is made by Behrman and Rosenzweig (2002) who,

[2] Had we elected instead to present our results in terms of non-linear relationships, the focus would have naturally fallen on whether non-linearities are significant, not whether partial derivatives themselves are significant.

using twin data from the US, find considerable evidence of assortative matching on education.[3] In their study, the relationship between father's education and child schooling is strong and large in magnitude, but the association with maternal education is not significant.

To investigate this in our dataset, we recalculate partial derivatives of father's and mother's education correcting for matching. Once we correct for the fact that a better educated mother is likely to marry a better educated father, the beneficial partial derivative of mother education on child welfare gets smaller in magnitude. This is due to non-zero cross-partials of mother and father education. At least part of the predictive power of mother education on child welfare is driven by marriage market effects and higher father education.

We then decompose the predictive power of parental education into aggregate and individual components, i.e., we add controls for the *average* education level of the age cohorts of the mother and father in their respective birth district and ethno-caste group. If the correlation between parental education and child welfare is driven primarily by labor markets externalities and other general equilibrium effects,[4] we expect the average education of the cohort to soak up much of the predictive power of parental education. This is not what we find: partial derivatives of father and mother education on child welfare are virtually unaffected. Average education levels of the mother and father age cohorts do, however, have a predictive power of their own. Controlling for the individual education levels of the father and mother, a better educated male *cohort* is associated with higher child welfare: lower fertility, higher survival rate, higher school attendance and educational attainment, and less child work. The same is not true for the female cohort: mothers from a better educated marriage cohort tend to have more children, a lower child survival rate, less child schooling, and more child work.

Next we seek to disentangle individual education from ability and family background. The literature has sought to deal with this issue by instrumenting mother's education.[5] Since this strategy is not avail-

[3] See also Breierova and Duflo (2004) and Carneiro, Meghir and Parey (2007).
[4] E.g., a fall in the average ability of the marginal degree holder as education levels increase.
[5] In developed countries, examples of this strategy can be found in the works of Black, Devereux, and Salvanes (2005), Oreopoulos and Page (2006), Chevalier (2004), Chevalier, Harmon, O'Sullivan, and Walker (2005), Maurin and McNally (2005), and Galindo-Rueda (2003) who exploit changes in compulsory schooling or in examination standards as instruments. Carneiro, Meghir and Parey (2007) use schooling costs during the mother's adolescence as instruments and find that mother's schooling increases child performance on standardized tests and reduces the incidence of behavioral problems. In developing countries, Andrabi, Das and Khwaja (2009) use the supply of gendered public schools in the mother's birth village as instrument. A similar instrumentation strategy is adopted for Indonesia by Breierova and Duflo (2004), who use time- and region-varying exposure to a school construction program as instrument.

able to us, we seek instead to decompose individual education into a relative ability component and a pure education component. The assumption behind our decomposition is that, within a relevant cohort, more academically inclined individuals (and individuals from a more supportive family environment) receive relatively more schooling even though their absolute level of schooling depends on general conditions such as school supply and local demand for educated workers. To implement this idea, we construct two proxies (i.e., for mother and father) for individual ability and family support calculated as the relative educational rank of an individual within their age cohort in their respective birth district and ethno-caste group.

When we add the educational rank of the mother and father as additional regressors, we find large changes in the residual predictive power of parental education on child welfare. Going from no education to some primary education is now associated with a small or zero increase in fertility for both mother and father, although the partial derivative remains negative above secondary education levels. We also find that, conditioning on age, mothers with more than primary education are more likely to have a child in the year preceding the survey – possibly capturing a fertility catching up effect. The partial derivative of child survival with respect to father education remains large for schooling above primary, but it is much smaller and hardly distinguishable from zero for mother education. For school attendance, the partial derivative with respect to father education is halved while that for mother education is now non-significant for primary education and negative for secondary education and above. A similar pattern is obtained for educational attainment. Finally, for child work, partial derivatives with respect to parental education are either zero or have the wrong sign. The change is particularly strong when we correct for assortative matching by education, in which case both father and mother education above primary are associated with more child work, not less.

In contrast, the educational *rank* of the mother in her marriage cohort is systematically and strongly associated with lower fertility, higher child survival rate, better child education, and less child work. The father's educational rank shows a less systematic correlation: it is strongly associated with higher school attendance and educational attainment and with less child work, but is positively correlated with fertility and uncorrelated with child survival rate. To the extent that the educational rank proxies for individual ability and family background – and not the causal effect of education itself – these findings suggest that much of the correlation between mother education and beneficial child welfare may not be attributable to education. On the other hand, the correlation between father education and child welfare remains even when we control for educational rank. Thus, even if educational rank over-controls for ability and family background, the fact that partial derivatives with respect to father education remain significant suggests that the correlation is probably not purely due to ability or family background – and is more likely to have a causal element. We cannot reach the same conclusion for mother education.

How do these findings compare to the literature? In a developed country context, Currie and Moretti (2003) find that maternal education has significant effects on birth-weight and gestational age while Breierova and Duflo (2004) find that, in Indonesia, female and male education seem equally important factors in reducing child mortality. This is consistent with our finding that parental education is associated with higher child survival rates.

We find that better educated parents have better schooled children who are less likely to work, but that the correlation is stronger for father than mother education once we proxy for innate ability. This is consistent with the findings of Behrman and Rosenzweig (2002, 2005) who, using a very different methodology, also find evidence that father education matters more than mother education for child schooling. Plug (2004) similarly finds weak effects of adoptive mother's schooling on child's schooling but large effects of father's schooling, while Bjoerklund, Lindahl, and Plug (2006) find strong effects of both adoptive father and mother's schooling. Amin and Behrman (2011) find, as we do, that cross-section correlations overestimate the effect of mother schooling on fertility.

In contrast, Sacerdote (2002) argues that a college educated adoptive mother is associated with a 7% increase in the probability that the adopted child graduates from college. For Guatamala, Behrman, Murphy, Quisumbing, and Yount (2009) find strong effect of mother intellectual capital on child schooling but note that a well-designed intervention 'require[s] approaches that account for dimensions of women's human capital beyond just their schooling'. Based on evidence of this kind, Holmlund, Lindahl, and Plug (2006) argue that results from the literature are quite disparate and a consensus has not formed yet. The evidence presented here cautiously suggests a possible reconciliation, namely, that conflicting results may be due to partial derivatives that vary by education levels in the respective study populations.

The paper is organized as follows. In section 2 we introduce the conceptual framework and testing strategy. The data are presented in Section 3 while Section 4 is devoted to empirical results.

2. Empirical strategy

The object of this paper is to study the statistical association between welfare and male and female education. The main focus is on the partial derivative of an additional year of male or female education on fertility and child welfare outcomes, and how this partial derivative varies by education level. We limit our attention to married couples.

2.1. Partial derivatives

We wish to ascertain whether an additional year of parental education is associated with different household outcomes regarding fertility and child welfare. Formally, let y denote an outcome of interest, m denote the education of the male parent (i.e., father), and f the education of the female parent (i.e., mother). We write:

$$\widehat{y} = g(f, m, v)$$

where $\widehat{y}$ is the predicted value of y, v denotes local conditions such as the supply of health and education, and $g(.)$ represents a sample multiple least squares regression (Goldberger, p.95).

We focus our analysis on the partial derivatives (PD) of $g(.)$ with respect to m and f. There are several reasons for this. First, PDs are more directly comparable to marginal treatment effects. Although our PDs cannot be given a causal interpretation in the way treatment effects can, presenting them in the same manner facilitates comparison. Secondly, we are interested in whether PDs are significant or not, something that is obscured if we present results in terms of the non-linearity of $g(.)$. Indeed, in that case the focus naturally falls on whether the non-linearity is significant, not whether PDs are different from 0. Third, thinking in terms of PDs opens the door to discussing assortative matching, a point to which we return below.

We wish to estimate $\frac{\partial \widehat{y}}{\partial f} = g_f$ and $\frac{\partial \widehat{y}}{\partial m} = g_m$ in a model sufficiently general to allow for $g(.)$ functions other than additively separable in m and f.[6] In particular, we wish to know the extent to which the PD of $\widehat{y}$ with respect to f is increasing or decreasing in m, i.e., whether for $\frac{\partial \widehat{y}^2}{\partial m \partial f} = g_{mf} \neq 0$. This issue is related to the question of whether mother and father education are complement or substitutes in the production of outcome y.[7]

Because educated women tend to marry educated men and vice versa, we distinguish two types of PDs. The first kind evaluates $\frac{\partial g(f,m)}{\partial f}$ at the average level of male education $\overline{m}$, i.e.:

$$g_f^u(f) \equiv g_f(f, \overline{m}, v) \tag{2.1}$$

For instance, if $g(f, m, v)$ is estimated as $\widehat{\alpha} + \widehat{\beta}_1 f + \widehat{\beta}_2 m + \widehat{\beta}_3 f^2 + \widehat{\beta}_4 fm + \widehat{\beta}_5 m^2 + v$ then:

$$g_f^u(f) = \widehat{\beta}_1 + 2\widehat{\beta}_3 f + \widehat{\beta}_4 \overline{m} \tag{2.2}$$

This is the derivative of the predicted value of y with respect to female education if women marry someone selected at random from the entire population of fathers.

In practice, there is assortative matching on education between husband and wife. In our data, the correlation in parental education is 0.63. A second kind of PD measures the change in $\widehat{y}$ that is associated with an increase in f, correcting for the fact that women with a higher f also have a better educated husband on average. If f and m are correlated and $g_{mf} \neq 0$, the two concepts are different. Formally, let $m(f)$ denote the sample of men married to women with education level f and let $\overline{m}(f)$ denote the sample mean of $m(f)$. The PD is defined as:

$$g_f^c(f) \equiv g_f(f, \overline{m}(f), v) \tag{2.3}$$

[6] In Stata $\frac{\partial \widehat{y}}{\partial f}$ is called a 'marginal effect'. We refrain from using the expression here because it implies causality and this causes confusion.

[7] To illustrate, suppose that outcome y increases in f and m and let $h(f, m)$ be the production function of y. If m and f are complement in the production of outcome y, we have $h_{mf} > 0$. In contrast, if $h_{mf} < 0$, this indicates that female education f is not indispensable to raise outcome y but can be substituted for by higher male education m. If $h_{mf} = 0$, both m and f raise y independently of each other. This is what is typically assumed in regression analysis of the relationship between parental education and household welfare outcomes. Although the data that we have precludes a direct estimation of $h(f, m)$, we nevertheless expect that $g_{mf} > 0$ whenever $h_{mf} > 0$.

In $g_f^c(f)$ $\overline{m}$ is conditional on the value of f while in $g_f^u(f)$ it is not. PDs with respect to male education are defined in a similar fashion.[8]

The importance of the distinction between $g_f^u(f)$ and $g_f^c(f)$ is best illustrated with an example. Suppose the parents of a little girl decide to educate her to improve her prospect in life. Assortative matching on education helps them achieve their objective. Assortative matching benefits vanish, however, if all parents do the same thing: when all daughters are better educated, they compete for an unchanged supply of grooms, and the additional benefit of marrying a more educated husband evaporates. Given this, the benefits of assortative matching should be included when making a policy recommendation to one set of parents, but not when making a policy recommendation to all parents. The same distinction arises when considering the scaling up of any intervention. See for instance Duflo (2004) for a good discussion of this issue in the context of education expansion in Indonesia.[9]

If parental education is correlated, from (2.2) we see that $g_f^c(f) \neq g_f^u(f)$ whenever $g_{mf} = \beta_4 \neq 0$. The difference between $g_f^u(f)$ and $g_f^c(f)$ is the part of the correlation between mother education and child welfare $g_f^u(f)$ that is driven by a correlation between mother and father education in married couples. It measures the role of the marriage market in the correlation between f and $\widehat{y}$. For this reason, we say the first kind of derivative has no (marriage market) assorting while the second corrects for assortative matching of the parents in the marriage market. If f and m are complement or substitute, the difference between the two can be sizeable. When $g_f^c(f)$ is much smaller than $g_f^u(f)$, the child welfare/mother education relationship can be overstated unless the researcher adequately controls for correlation in parental education.

[8] In the empirical analysis $g(f, m, v)$ includes other cross terms as well. They are handled in a similar fashion. To illustrate, let w_i be the mother's age and d_i another relevant characteristic of the mother. We have:

$$\begin{aligned}
g(f_i, m_i, v_i) &= \widehat{\alpha} + \widehat{\beta}_1 f_i + \widehat{\beta}_2 m_i + \widehat{\beta}_3 f_i^2 + \widehat{\beta}_4 f_i m_i + \widehat{\beta}_5 m_i^2 + \widehat{\beta}_6 w_i f_i + \widehat{\beta}_7 d_i + \widehat{\beta}_8 d_i f_i + \widehat{v}_i \\
g_f(f_i, m_i) &= \widehat{\beta}_1 + 2\widehat{\beta}_3 f_i + \widehat{\beta}_4 m_i + \widehat{\beta}_6 w_i + \widehat{\beta}_8 d_i \\
g_f^u(f) &= \widehat{\beta}_1 + 2\widehat{\beta}_3 f + \widehat{\beta}_4 \overline{m} + \widehat{\beta}_6 \overline{w} + \widehat{\beta}_8 \overline{d} \\
g_f^c(f) &= \widehat{\beta}_1 + 2\widehat{\beta}_3 f + \widehat{\beta}_4 \overline{m}(f) + \widehat{\beta}_6 \overline{w}(f) + \widehat{\beta}_8 \overline{d}(f)
\end{aligned}$$

As before $g_f^u(f)$ is linear in f while $g_f^c(f)$ is not.

[9] In her case, matching is between a worker and a job. But the reasoning is the same: when more people get educated, there is more competition for jobs that require education. Hence the benefit from acquiring education depends on whether others acquire education as well, and the anticipated benefit from education at the individual level does not necessarily scale up to the whole population.

2.2. Further decomposition

It is widely recognized that correlation between parental education and household outcomes does not imply causation. Two major sources of confounding effects have been discussed in the literature: general equilibrium effects, and unobserved individual heterogeneity. We construct proxy variables for both in an effort to decompose the correlation between y and education into various components, i.e.: variation associated with education at the level of individual parents; variation associated with a higher educational level of parents in a given area; and variation due to ability and family background but correlated with individual education. Examples of effects falling into the first component include higher parental income and better health knowledge. Examples falling into the second include higher local development, better amenities, health externalities, and school peer effects. Examples falling into the third include smarter and more attentive parents and grand-parents, irrespective of their education.

More educated parents are, on average, surrounded by other more educated parents, either over space (e.g., urban inhabitants are on average more educated) or time (e.g., younger cohorts are on average more educated). To capture this idea with the data at hand, we construct variables F and M that represent the average level of male and female education in the birth cohort of each father and mother in our dataset. Space and time may also have direct aggregate effect on fertility and child welfare, e.g., because of better public amenities or higher incomes. These phenomena could account for part of the correlation between y and average parental education. If g_f^u and g_f^c become smaller in magnitude once we control for F and M, this indicates that part of the correlation of interest is driven by aggregate – not individual – factors. This does not necessarily imply that education is unimportant from the point of view of policy makers, only that the channel by which it raises child welfare involves unspecified general equilibrium effects and externalities, not a response at the level of individual parents.

Unobserved individual heterogeneity is also a source of concern, particularly parental attributes that are correlated with education and have a causal impact on y. Examples include individual ability (e.g., intelligence and non-cognitive skills) and family background: we expect smarter mothers and fathers to take better care of their children, and people encouraged to stay in school by their parents may also be encouraged to take good care of their offspring (e.g., Behrman and Rosenzweig 2002).

We do not observe individual ability and family background but, if we are willing to make some assumptions, we can derive a reasonable proxy for it. The assumption behind our proxy is that, within a relevant marriage cohort – i.e., among people of the same age, birth district, and ethno-caste – individuals who are more academically inclined and come from a more supportive family receive more schooling relative to others. It follows that their absolute level of schooling depends on time-varying district conditions such as school supply and demand for educated workers, but their relative level is driven primarily by ability and family background.

If this assumption is correct, we can use the educational attainment rank of an individual in their birth cohort as proxy for individual ability and family background – or more precisely for the part of individual ability and family background that is correlated with education.[10] Let R_f and R_m denote the education rank of each parent in their respective birth cohort. If g_f^u and g_f^c falls in magnitude after we control for R_f and R_m, this suggests that part of the correlation between parental education and y may be due to unobserved individual heterogeneity in ability and family background, not to education per se.

We also seek to control for variation in marriage market conditions that may affect our outcomes of interest. Marriage markets have received less attention as possible confounding factors affecting the correlation between parental education and household outcomes. Yet they too could play a role.

It is widely believed that women on average wish to have fewer children than men (see Ashraf and Field 2011 for recent experimental evidence), but also that mothers wish to take better care of the children they have than fathers do (e.g., Becker, Murphy and Tamura 1990, Fafchamps, Kebede and Quisumbing 2009). The works of Porter (2010) and Arcidiacono, Beauchamp, and McElroy (2011) further suggest that women are more empowered when they are in scarce supply in the marriage market. If this is true, women in a more advantageous marriage markets may be more successful in seeing their preferences reflected in household decisions about fertility and child welfare. This is especially true if they are better educated than other potential brides in their cohort. A similar, mirror argument can be made for men. It follows that part of the correlation between parental education and household outcomes such as fertility and child welfare could be driven by marriage markets.

[10] The part that is not correlated with education is not a source of bias and is subsumed in the error term.

To capture this possibility, we construct two indicators of marriage market conditions. The first indicator G measures the relative proportion of potential brides and grooms in each parent's birth cohort. The second indicator E measures the relative average education of potential brides and grooms in each parent's birth cohort. We expect women to have a better bargaining power in marriage markets with fewer women relative to men, and where the average education gap between men and women is smaller. It follows that the correlation between G and E with y is expected to reproduce differences in preferences for y between men and women. We also interact G and E with individual education to proxy for a possible marriage market effect of education on y through better intrahousehold bargaining.

3. The data

We use data from the 2001 Nepalese population census. The short population census questionnaire was administered to the whole population. It contains information about many demographic variables, such as the number of dead and surviving children of both sexes. For each child, we have information about their age, gender, school attendance, and education level. The census also recorded whether the child worked in the 12 months preceding the census. The census contains information about the ethnicity of the parents and their spoken language.

For a randomly selected 11% of the census population, additional information was collected using a second, longer questionnaire. This questionnaire collected information on district of current residence, district of residence 5 years prior to the census, and district of origin. Detailed information is also available on gender, age, education, unemployment, and occupation of the parents. The 11% population census covers approximately 2.5 million individuals in 520,624 households.

The Nepalese Central Bureau of Statistics was kind enough to merge the short and long questionnaire datasets for us. This provides a very large data set on which we estimate the partial derivative of male and female education. We focus on monogamous couples residing together at the time of the census – around 340,000 households. Most of these couples are married. To minimize data artefacts, we only keep couples in which both spouses are aged 60 or less.[11]

[11] Above sixty years of age, differences in survival rates between men and women generates too much bias in marriage market proxies (see below).

Nepal is a good choice to study the partial derivative of female education. In terms of culture and attitudes, it is similar to its large Southern neighbor, India, with a population that is primarily Hindu. Hence results for Nepal are probably informative about Northern India, and perhaps about other countries in the sub-region as well. Because Nepal is very mountainous, it remained geographically isolated for a long time. Things are changing rapidly, however. Education levels have increased steadily in the recent past, and the education gap between boys and girls is closing. But there remain important disparities in education across individuals.

We focus our analysis on two groups of dependent variables for which information is available: fertility and child survival; and child education and child labor. Since we limit our analysis to co-residing monogamous couples, each household includes a 'husband' and a 'wife'.

Census questions about fertility and child mortality were only asked to women between the age of 16 and 49. They refer to the household as a whole, not to individual children. As measures of fertility we use the total number of reported sons and daughters and a dummy variable that is equal to 1 if the wife of the household head had a live birth in the 12 months preceding the census. For child mortality, we use the proportion of sons and daughters born to the wife who are still alive at the time of the census. We do not have information on the age at which a child died.

Table 1 presents descriptive statistics for these household-specific dependent variables. Across all households with at least one son or one daughter, the average survival rate for sons and daughters is around 94% – slightly lower for daughters. The number of ever born children reported by each household is on average higher for boys than for girls. We also note the smaller number of households that report having at least one daughter. These figures suggest that there could be underreporting of daughters' births (and death) – although we cannot be sure (e.g., Anderson and Ray 2010).[12] For all women of childbearing age, the census recorded whether they had a live birth in the 12 months preceding the survey. On average, the wife of the household head had a live birth in 6.4% of the households in the sample.

Table 1 shows descriptive statistics for the regressors used in the household outcome analysis. Average

[12] The smaller number of households reporting having at least one daughter could be because of a parental stopping rule. If households who get a son first stop while households who get a girl first keep trying until they get one son, there will be more households with at least one son than households with at least one daughter.

education levels for husbands and wives, measured in years of schooling, are low but slightly higher for men. 40% of husbands and 70% of wives have no education at all. The correlation in education levels between husband and wife is 63%. On average a husband in a monogamous couple is 4.7 years older than his wife; the corresponding median is 4 years.

When estimating (2.1) and (2.3) we need to control for local conditions such as health risk factors and the provision of educational and health services. To do so, we include locality fixed effects at the point of residence. Nepal is divided into 75 districts and further subdivided into 3915 Village Development Council or VDCs. All the regressions presented here include fixed effects for the VDC of residence.[13] In addition, standard errors are clustered by VDC to correct for possible negative correlation in outcomes within VDCs.

We include dummies for the main language, religion, and ethnicity of the husband and wife. For language, the dummy takes value 1 if Nepali, the national language, is the person's mother tongue. This dummy is included as control because parents who speak the national language may be in a better position to understand health and nutrition instructions received from teachers and health practitioners. Nepali is the mother tongue of half of the husbands and wives. The religion dummy takes value 1 if the person is Hindu, and 0 otherwise. For caste/ethnicity, we rely on the classification used by the Nepalese Central Bureau of Statistics in its surveys. This classification, which is quite detailed, combines caste-like categories with tribal affiliation. In Table 1 we define dummies corresponding to each of the three main categories, Brahmin, Chhetri, and Newar; individuals who are neither get coded as 0. Close to 16% of respondents classify themselves as Brahmin or Chhetri, while another 8% classify themselves as Newar. Together these three categories account for 40% of the sample.

Marriage market variables are presented next. Most Nepalese couples report sharing the same language, religion and ethnicity. For instance, in 99.7% of the couples where the husband reports being Hindu, the wife is also reported as being Hindu. Similarly, in 99.2% of the couples for which the husband is reported as not Hindu, his wife is not Hindu either. For speaking Nepali, the equivalent proportions are

[13] The purpose is to purge the correlation between parental education and household outcomes that may be due to residence – e.g, health care provision, school supply. Doing so takes out one possible channel – migration – through which parental education may affect child welfare. Given that the overwhelming majority of individuals in the data live in their birth district, this is not much of a concern.

99.4% and 99.1%. Equally high – if not higher – proportions are reported for ethno-caste affiliation. To capture this reality, we divide all individuals born in a given district into marriage cohorts based on caste and religion. Doing so is a delicate balancing act: narrowly defined categories identify potential mates more precisely,[14] but they lead to small marriage cohorts. To minimize the resulting measurement error, we keep the number of categories to five. Non-Hindus constitute one category, representing around 17% of the population. Hindus are then divided into the three caste groups listed above (e.g., Brahmin, Chhetri, and Newar) and a residual category made of other Hindus. Except in large urban centers, non-Hindus in a given district tend to belong to the same religion. Similarly, other Hindus tend to come from a small number of castes.

The age cohort of each individual i is defined as the set of same age and same gender individuals (married or unmarried) who potentially compete for mates in the same marriage pool. There is severe bunching in the age data, with spikes in the age pyramid at all multiples of five. For this reason we construct cohorts to include the five age categories closest to i. For instance, the cohort of a 22 year old woman includes all relevant women aged 20 to 24 while the cohort of a 23 year old woman includes relevant women aged 21 to 25. It follows that each cohort only includes a single age that is a multiple of 5.

The marriage cohort of individual i is then defined as all individuals who: (1) have the same gender; (2) belong to the same ethno-caste category defined above; (3) have the same birth district; and (4) are no more than two years older or younger than i. This definition is used throughout the analysis whenever we refer to the cohort of individual i.

To proxy for female scarcity in the marriage market we proceed as follows. Let N_j^f denote the above-defined female cohort of woman j. Let the cohort of potential mates for j be written as N_j^m, defined as all individuals who: (1) are male; (2) belong to the same ethno-caste category; (3) have the same birth district; and (4) are no more than 7 and no less than 3 years older than woman j. To minimize data artefacts driven by age bunching, we have assumed that the age cohort of husbands is on average five

[14] Correlation in narrowly defined caste groupings across husband and wife is extremely high in the data, suggesting severe segregation in the marriage market. It is however possible that the caste that spouses report to census enumerators has been 'adjusted' to fit the social norm of endogamous marriage.

years older than the cohort of relevant wives. This is reasonably close to the average age gap which is 4.7 years.

Of course, j need not marry someone in N_j^m – she may marry someone born in another district, from another marriage pool, or who is the same age as her. But N_j^m represents the 'natural' marriage pool of j. If $N_j^m > N_j^f$, there are more men than women in j's natural marriage pool, which we assume empowers j and ensures her preferences are better represented in household choices. Similarly for a man k: if $N_k^f > N_k^m$, k competes with fewer other men for women in his cohort, and this is assumed to empower him.

Consider a couple i formed of individuals j and k. If people do not marry within their cohort someone exactly 5 years apart, $N_j^m \neq N_k^m$ and $N_j^f \neq N_k^f$.[15] To reflect this, we combine information from both the husband and the wife's natural marriage cohorts to construct the female scarcity variable dn_i of couple i defined as:

$$dn_i = \frac{N_j^m + N_k^m - N_j^f - N_k^f}{N_j^m + N_k^m + N_j^f + N_k^f}$$

By construction dn_i is normalized to lie between -1 (extreme female competition) to $+1$ (extreme male competition). A value of 0 means an equal number of men and women in the marriage cohorts of couple i. The average value of dn_i is -0.08 in our population of couples, indicating that there are on average more women than men in a given marriage cohort. This is mostly due to the age difference between married men and women, combined with rapid population growth.

We also construct a marriage market variables proxying for the average imbalance in education levels between brides and grooms. Let E_j^m denote the average educational level of individuals in N_j^m, and similarly for E_j^f. The imbalance in average education level for couple i is defined as:

$$de_i = \frac{E_j^f + E_k^f - E_j^m - E_k^m}{2}$$

It is measured in terms of years of education. The average value of de_i is -2.29, implying that men have on average 2.29 years of schooling more than the women in their marriage cohort. Both dn_i and de_i are

[15] They are the same if the wife is exactly five years younger than her husband and they have the same birth district and marriage pool.

constructed such that an increase implies marriage market conditions more favorable to women.

Next we report F and M, the average level of male and female education in the birth cohort of each father and mother in our dataset. For each spouse we report two numbers as follows, one centered on the husband's age, and the other on the wife's age.[16] The two are not very different but we use both as controls to net out, in some of our regressions, the partial derivative of individual education. As expected, years of education are higher on average for men than for women. The educational ranks R_m and R_f of men and women in their respective marriage cohort are reported next. As explained earlier, R_m and R_f proxy for unobserved heterogeneity in ability and family background. The average rank is, unsurprisingly, close to 0.5, with healthy variation around the mean. The remainder of Table 1 presents individual characteristics of the husband and wife. Parental education is the focus of our analysis. The other regressors serve as controls.

Table 2 reports descriptive statistics for child specific dependent variables. Child education and child labor are recorded for each child separately, but are limited to those children residing in the household at the time of the census. School attendance is a 0-1 variable equal to 1 if the child was attending school around the time of the census. We also have information on the number of completed years of education. School attendance and completed education are only recorded for children between the age of 6 and 15. For children aged 10 and above, we also have a report by the parents on the number of months during which the child worked in the 12 months preceding the census. Here "work" refers to wage employment or work on the family farm or business. As documented by Fafchamps and Wahba (2006), child labor is common in rural Nepal, and mostly involves helping on the family farm or business.

As shown in Table 2, a little over three quarter of the children in the sample are reported as attending school at the time of the census. The number of years of education, averaged over all the children in the sample, is 2.5. For children aged 10 to 15, the average number of months worked during the last 12 months is one.

We control for a number of child-specific variables. The average age of the child in the sample is 10.3.

[16]Let w_m and w_f be the age of the husband and wife, respectively. The first value of M is the average education of men aged $w_m - 2$ to $w_m + 2$ in the husband's cohort. The second value of M is the average education of men aged $w_f + 5 - 2$ to $w_f + 5 + 2$, that is, using the wife's age to center the cohort. If $w_m = w_f + 5$ the two concepts coincide. In the data the two calculations yield very similar values. A similar approach is used for F.

48% of children are girls. To control for household composition effects and possible sibling competition for resources, we include controls for the number of male and female co-residing elder siblings.[17] Older siblings can help parents around the house or household business and thus help younger siblings to attend school and dispense from work. The average child in the sample has 0.72 older male siblings and 0.6 older female siblings co-residing in the household. The proportion is lower for female siblings presumably because girls marry earlier, at which time they leave the household.

The census also recorded information on whether the child is living with his/her biological parents or not. Most children (88.7%) live with both biological parents; 6.69% of children live with their biological mother while 2.45% live with their biological father. The rest (2.16%) do not live with their biological parents and are ignored from the analysis. We also limit our analysis to children living with a married couple, so that we have information on both husband and wife. In this subsample, 96.7% of the children live with both their biological parents.

In the children regression we also control for household size and dependency ratio. As seen in Table 2, the average child in the sample lives in a household with 6.3 members, half of which are children. There is considerable variation across households in terms of size and dependency ratio (i.e., the number of children divided by total household size).

[17] We experimented with other sibling composition variables, such as rank or total number of male and female siblings. But using older siblings gives the best fit.

4. Empirical results

For household-specific variables, we begin by estimating a short model of the following form:

$$\begin{aligned} y_{iv} &= \beta_0 m_{iv} + \beta_1 m_{iv}^2 + \beta_3 f_{iv} + \beta_4 f_{iv}^2 + \beta_5 m_{iv} f_{iv} \\ &\quad + \alpha_0 h_{iv} + \alpha_1 h_{iv}^2 + \alpha_3 w_{iv} + \alpha_4 w_{iv}^2 + \alpha_5 h_{iv} w_{iv} \\ &\quad + \gamma_1 m_{iv} h_{iv} + \gamma_2 f_{iv} w_{iv} \\ &\quad + \theta_0 dn_{iv} + \theta_1 dn_{iv}(m_{iv} - \overline{m}) + \theta_2 dn_{iv}(f_{iv} - \overline{f}) \\ &\quad + \lambda_0 de_{iv} + \lambda_1 de_{iv}(m_{iv} - \overline{m}) + \lambda_2 de_{iv}(f_{iv} - \overline{f}) \\ &\quad + \sum_d \delta_d D_{iv} + u_v + \varepsilon_{iv} \qquad (4.1) \end{aligned}$$

where y_{iv} denote an indicator of interest for household i in VDC v. As in Section 2, m_{iv} and f_{iv} denote the education level of the husband and wife while d_{iv} stands in for the two marriage market variables. Variables h_{iv} and w_{iv} denote the age of the husband and wife, respectively. Language, religion, and ethnicity dummies, for both the husband and the wife, are represented by D_{iv}. The regression includes a VDC fixed effect u_v. Robust standard errors, clustered by VDC, are reported throughout.

For child-specific variables such as school attendance, education, and child work, the regression model (4.1) is expanded to include child-specific age and gender dummies, the log of household size, the dependency ratio (calculated as the share of children in the household), the number of older male and female co-residing siblings, and whether the child lives with only a biological mother or father. For school attendance and attainment, children aged between 6 and 15 are included. The child work question was only asked for children aged 10 and above.

Model (4.1) is quadratic in m_{iv} and f_{iv}. To ensure our results are not an artefact of this functional form, we also estimate a version of (4.1) with a cubic term in m_{iv} and f_{iv}, as well as a fully saturated model in m_{iv} and f_{iv}. In the following pages we focus our presentation on model (4.1) but we discuss the results obtained with the two alternative models whenever relevant.

4.1. Partial derivatives

Estimated coefficients for the household short regressions are summarized in Table 3; those for children regressions appear in Table 4. Our interest lies in estimating partial derivatives or PDs with respect to parental education for each of the dependent variables. Since partial derivatives vary with f and m, they are best represented graphically.

We begin with the survival rate of daughters. Estimates of PD for the husband's education are reported on the left-hand panel of Figure 1 while the right-hand panel shows the same for the wife's education. In each panel two PD estimates are shown, each with its 95% confidence interval.[18] The second is $g_m^c(m)$ defined earlier, that is, allowing for assorting on the marriage market. The first is $g_m^a(m)$. It is the PD unconditional on the assortative matching of parents on education. It corresponds to $g_m^u(m)$ defined in Section 2. Formally we have:

$$g_m(f_i, m_i) = \widehat{\beta}_0 + 2\widehat{\beta}_1 m_i + \widehat{\beta}_5 f_i + \widehat{\gamma}_1 h_i + \widehat{\theta}_1 dn_i + \widehat{\lambda}_1 de_i$$

from which we define:

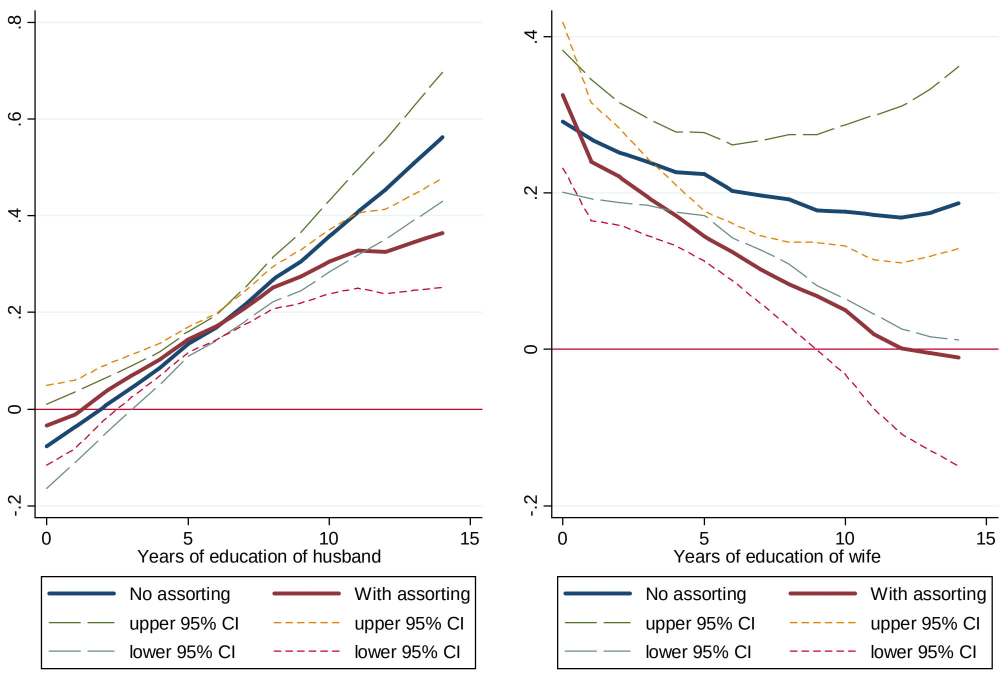
$$\begin{aligned} g_m^u(m) &\equiv \widehat{\beta}_0 + 2\widehat{\beta}_1 m_i + \widehat{\beta}_5 \overline{f} + \widehat{\gamma}_1 h(m_i) + \widehat{\theta}_1 \overline{dn} + \widehat{\lambda}_1 \overline{de} \\ g_m^c(m) &\equiv \widehat{\beta}_0 + 2\widehat{\beta}_1 m_i + \widehat{\beta}_5 \overline{f} + \widehat{\gamma}_1 h(m_i) + \widehat{\theta}_1 dn(m_i) + \widehat{\lambda}_1 de(m_i) \end{aligned}$$

Note that the above definition of $g_m^u(m)$ uses $h(m_i)$, the average age for males of education level m_i, not $\overline{h}$, the average over the entire sample. This is done to better visualize the difference in PDs that is purely due to assortative matching: any difference between $g_m^u(m)$ and $g_m^c(m)$ is only due to marriage market conditions. PDs with respect to female education $g_m^u(m)$ and $g_m^c(m)$ are calculated in a similar fashion.

The right-hand panel of Figure 1 shows in blue the unconditional PD of an additional year of female education. One additional year of education for an illiterate mother is associated with an increase in daughter survival probability by 0.2 to 0.35 percentage points. This is a large partial derivative given

[18] Partial derivatives are obtained using the `margins` command in Stata. Confidence intervals are corrected for clustering at the VDC level.

Figure 1: Partial Derivatives of daughter survival rate



that the average survival rate is around 94%. For instance, according to these estimates, mothers with 5 years of education are predicted to have lower daughter mortality by around 1 percentage point. The graph also shows that the unconditional PD falls with female education. This is because β_4, the coefficient of female education squared, is negative (see Table 3).

The panel also shows the conditional PD $g_f^c(f)$. Coefficient β_5 corresponds to the male and female interaction term $m_{iv}f_{iv}$ in (4.1). If male and female education are correlated (sample correlation is 0.63), for educated women we have $E[m_{iv}|f_{iv}] > E[m_{iv}]$. Consequently, other things being equal, if $\beta_5 < 0$ the conditional PD $g_f^c(f)$ is lower for educated women than the unconditional PD $g_f^u(f)$. This is to be expected: a negative β_5 means that the PD of female education falls with male education, something that could arise because male and female education are substitute in the production of daughter survival. Given that educated women are more likely to marry an educated man, $g_f^u(f)$ overestimates the correlation between female education and household welfare in the population at large.[19]

[19] A similar overestimation, subsumed in the calculation of $g_f^u(f)$, arises through the correlation between female age and education, which is negative (-0.24). This means that, for educated women, $E[w_{iv}|f_{iv}] < E[w_{iv}]$. Coefficient γ_2 corresponds to the female age-education interaction term $f_{iv}w_{iv}$ in (4.1). If $\gamma_2 > 0$, this generates an additional force in equation (**??**) that pushes $g_f^c(f_{iv})$ below $g_f^u(f_{iv})$. The intuition behind this result is simple. A positive γ_2 means that the

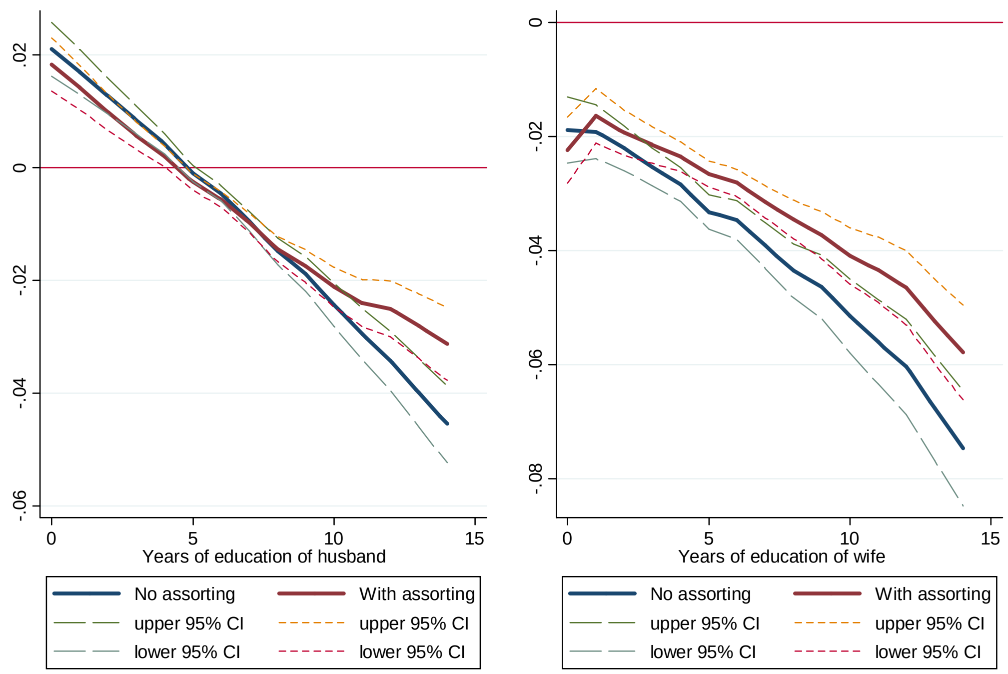
Given that $\beta_5 < 0$ for daughter survival (see Table 3), and given the sample correlations discussed earlier, $g_f^c(f_{iv}) < g_f^u(f_{iv})$ for educated women. This is what the right-hand panel of Figure 1 indicates: the PD falls faster with female education than the unconditional PD. If we also consider the confidence interval for both types of PD, we see that additional female education beyond 9th grade does not predict a higher daughter survival once we take into account the education level of the husbands that a more educated woman is likely to marry.

The left-hand panel of Figure 1 does the same thing for male education. The male and female panels are very different. For women, the PD of education is highest at low levels of schooling – e.g., primary and, to a lower extent, middle school. In contrast, for men the PD of schooling on daughter survival rates is zero at low levels of schooling but increases strongly with education. We also note that marriage market assorting is less an issue for males: the difference between $g_m^u(m)$ and $g_m^c(m)$ is smaller than for female education, except at high levels of male education. We calculated similar partial derivatives for son survival rates. The results, not shown here to save space, are very similar to those reported in Figure 1 for girls. If we include cubic terms in male and female education, results are qualitatively similar: PDs increase in father education and fall in mother education, and when we control for assorting they are not significantly different from zero for mother education above primary school. Similar qualitative results are found in the fully saturated model, although with more noise.

Next we look at fertility. We begin with the number of sons and daughters of the couple. PDs are summarized in Figure 2 for sons. The Figure for daughters is similar and is not shown here to save space. We see that the PD of female education on the number of sons is negative throughout (right-hand panel of Figure 2), but the PD is much more negative at higher levels of education. There is only a small difference between unconditional and conditional curves. For men (left-hand panel), male education is initially associated with a small positive PD on the number of sons – men with one or two years of primary education tend to have more sons than those with no education at all. The PD of male education becomes negative above primary education. This U-shaped relationship in father education is also clearly apparent

partial derivative of education is higher for older women. This may be because, in our sample, the few older women who managed to get some education were given information that was particularly useful to improve child survival at a time when health and nutrition conditions were poorer than they are now. Younger women are, on average, better educated but sanitary conditions may have improved, in which case the partial derivative of education of child survival could be smaller. This is what a significantly positive γ_2 suggests.

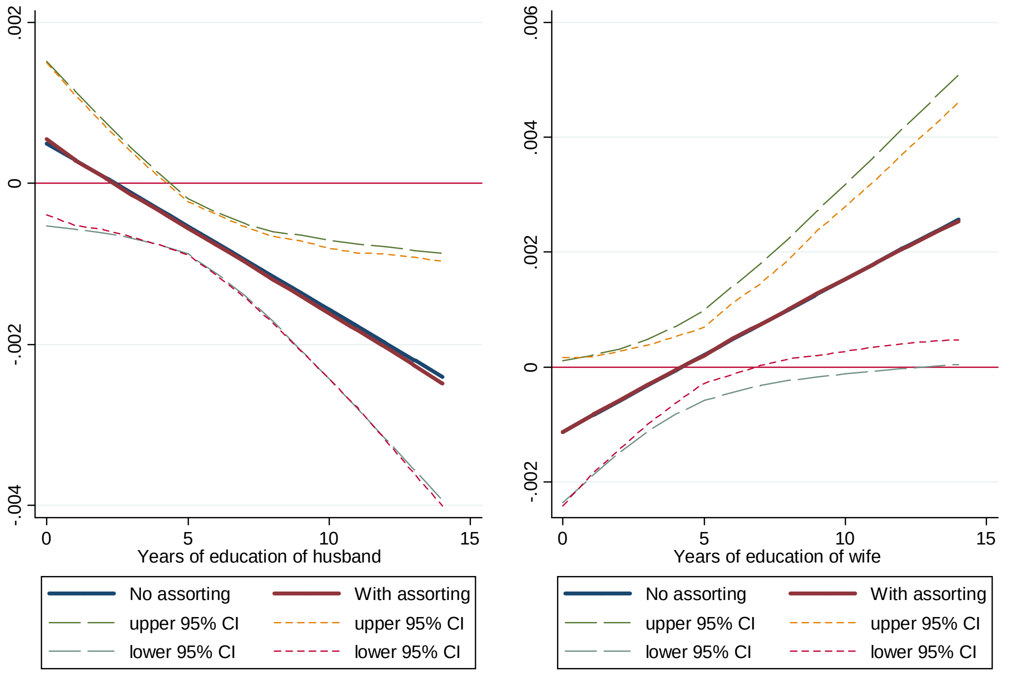
Figure 2: Partial Derivatives of total number of sons



in the cubic and fully saturated regressions.

Next we turn to childbirth in the 12 months preceding the census. Results are summarized in Figure 3. For male education, the PD is qualitatively similar to that for the number of sons and daughters, although not significant at low education levels. Female education, however, shows a markedly different pattern: instead of PDs becoming more negative with education, we observe an initially negative but non significant PD at small levels of education that turns into a positive PD at higher levels of female education. In other words, among poorly educated women, increasing education by one year is, if anything, associated with a weak reduction in the likelihood of having a child in the 12 months preceding the census, although this feature is not significant and disappears in the cubic model. But for women having completed primary education, one additional year of education is significantly associated with a small increased this likelihood. If we compare Figures 2 and 3 we get a very different picture regarding the PD of post-primary education on fertility. Taken together, the results indicate that a more educated woman of a given age has fewer children but is more likely to have had a child in the preceding year. This is may be due to a catching up effect, educated women having children later in their adult life (Amin and Behrman 2011).

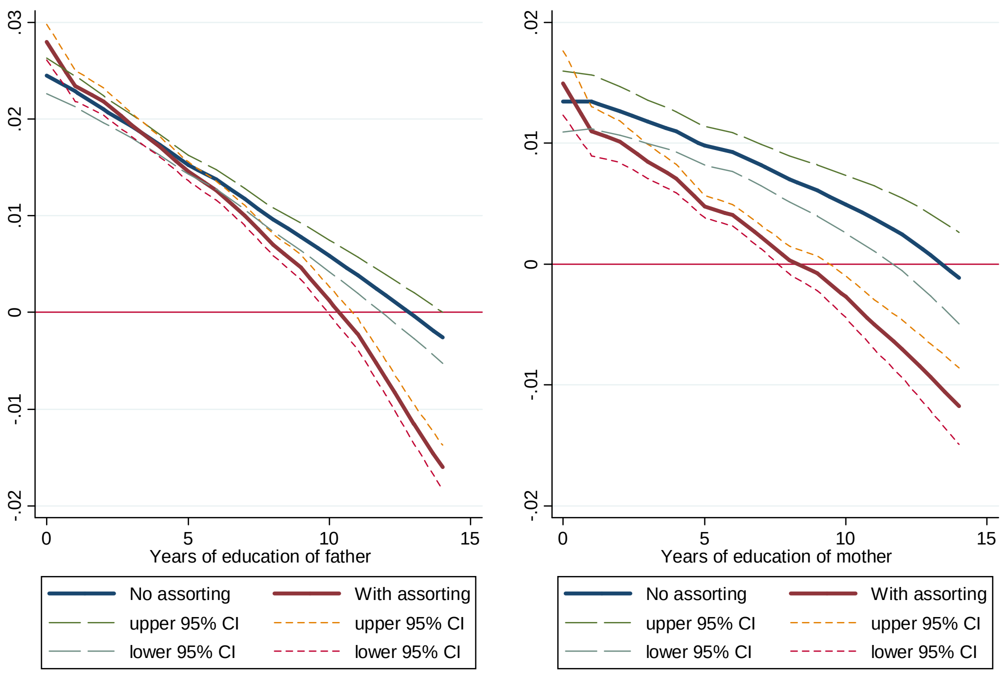
Figure 3: Partial Derivatives of the likelihood of live birth in past year



In Figure 4 we examine the relationship between child school attendance and parental education. Coefficients of the child-specific regressions are reported in Table 4. For memory, these regressions control for age and gender of the child together with VDC fixed effects and parental characteristics. From the left-hand panel of Figure 4 we see that the PD is high at low levels of father education but falls to zero for higher-secondary education levels of the father. Male PDs are not much affected by assortative matching, except at high levels of male education. The reader should not pay too much attention to the significantly negative PD at high levels of father education in the regression with assorting: it disappears in the cubic version of the model; other features remain.

The PD of mother education on school attendance is also large, albeit smaller than that of father education: the PD of going from no education to one year of primary education raises school attendance of children by around 2.5 percentage points for fathers but only by around 1.2-1.4 percentage point for mothers. We also note that assortative matching leads to a sharp reduction in the PD of mother education on child school attendance. In other words, in Nepal there is a stronger association between school attendance and father education than with mother education. We also note the negative PD

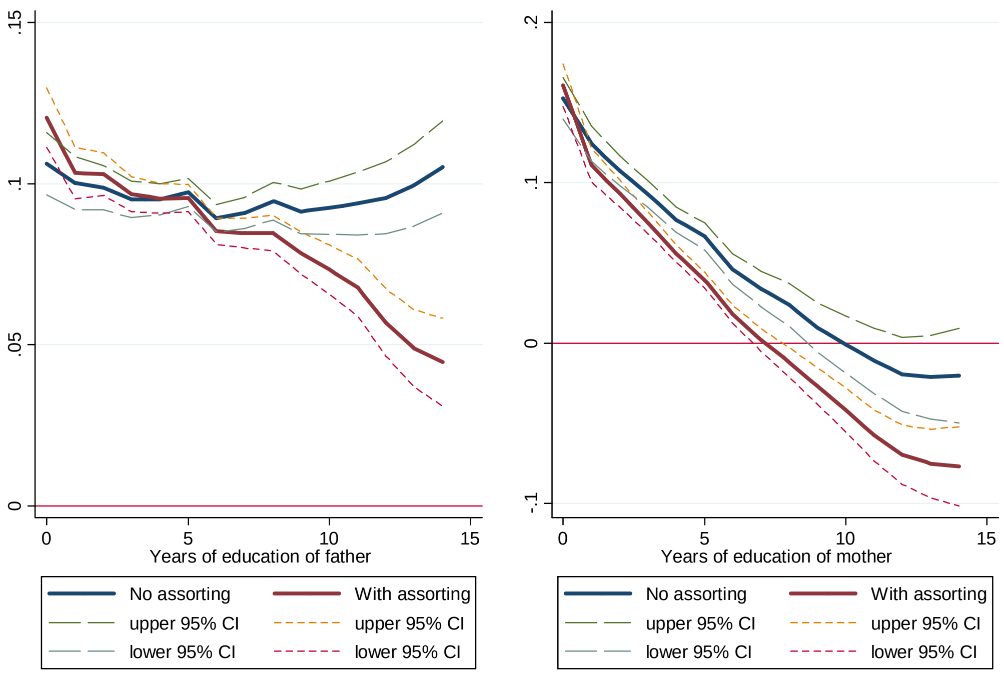
Figure 4: Partial Derivatives of child school attendance



at high enough levels of mother education in the regression with assorting. This feature can also be observed in the cubic and fully saturated models, although it tends to be limited to upper secondary school education. Why this is the case is unclear. One possibility is that more educated parents are more likely to be engaged in non-farm activities, either as wage employed or self-employed (Fafchamps and Quisumbing 1999). If they are self-employed, they may involve their teenage children in the business as a kind of apprenticeship; if they are wage employed, they are more likely to rely on older children to substitute for them at home and on the farm (Fafchamps and Wahba 2006).

The relationship between completed schooling and parental education is displayed in Figure 5. Here too we control for the age and gender of the child (see Table 4). The general pattern is similar to that observed for school attendance, although there are important differences. We again see a strong PD of father education on total schooling. The PD of female education is initially higher than that of men but falls more rapidly. PDs that correct for assortative matching fall more rapidly with education than unconditional ones. This is true for both fathers and mothers. This finding is in line with coefficient estimates reported in Table 4: β_5, the coefficient of the male-female education term, is significantly

Figure 5: Partial Derivatives of child years of schooling

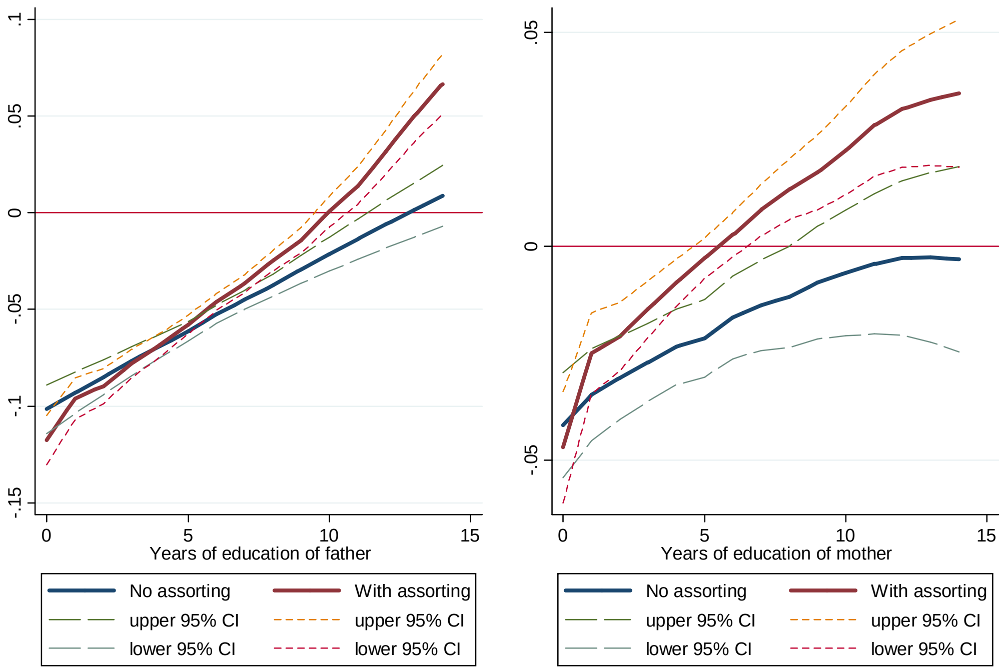


negative, hence the steeper conditional PDs. This suggests that male and female education may be substitutes as far as child schooling is concerned. As in Figure 4 we observe, in the regression with assorting, negative PDs on high levels of female education. This result is also present in the cubic and fully saturated models.

Do these results carry over to child work? The answer is yes, as we can see from Figure 6. Father education has a particularly strong negative association with the likelihood of that a child aged 10 to 15 worked in the 12 months preceding the census. This negative relationship disappears at higher levels of father education, probably because children of fathers with completed secondary education hardly ever work. Conditional and unconditional PDs are similar for father education.

The PD of mother education is also negative at low levels of education, but much smaller in magnitude. We also observe steeper conditional than unconditional PDs. The conditional PD of female education on child work is negative at low levels of education – i.e., below completed primary education – but positive for highly educated women – e.g., completed secondary and above, confirming earlier results on education. Since educated women are much more likely to work in our sample, this is consistent with the

Figure 6: Partial Derivatives of months of child work



idea that educated women involve their children in work outside the home, e.g., in their business.

Before presenting further regression results, we summarize in Table 5 unconditional partial derivatives from regression (4.1) averaged over the entire sample. These average PDs are similar to the parental education coefficient one would obtain by regressing outcomes linearly on father and mother education: they implicitly weigh PDs by the proportion of the sample in each education categories.

Since most mothers in our sample have no education, average PDs of female education are dominated by the partial derivative at 0 years of education. In contrast, PDs for male education are averaged over a broader range of education values. This is what we find: average PDs reported in the first row of Table 5 are larger for female than male education whenever female education PDs at low values are largest, such as for son and daughter survival (Figure 2) and for the number of sons and daughters (Figure 3). For other outcomes, the difference is less marked. What this suggests is that PDs obtained from simple linear regressions should be interpreted with caution.

In the next two rows of Table 5 we calculate average PDs separately for young and old parental cohorts, using the median age of the mother and father as cutoff. We note that average PDs are in general smaller in magnitude for young cohorts. Part of this difference is because younger cohorts are, on average, better educated and PDs of parental education tend to fall with education, as shown in several of the Figures above. Another part of the difference is driven by strongly significant interaction terms between age and education for males and females, as indicated in Tables 3 and 4. Together, these two factors explain why the improvement in household welfare indicators associated with increased parental education is much lower in younger cohorts.

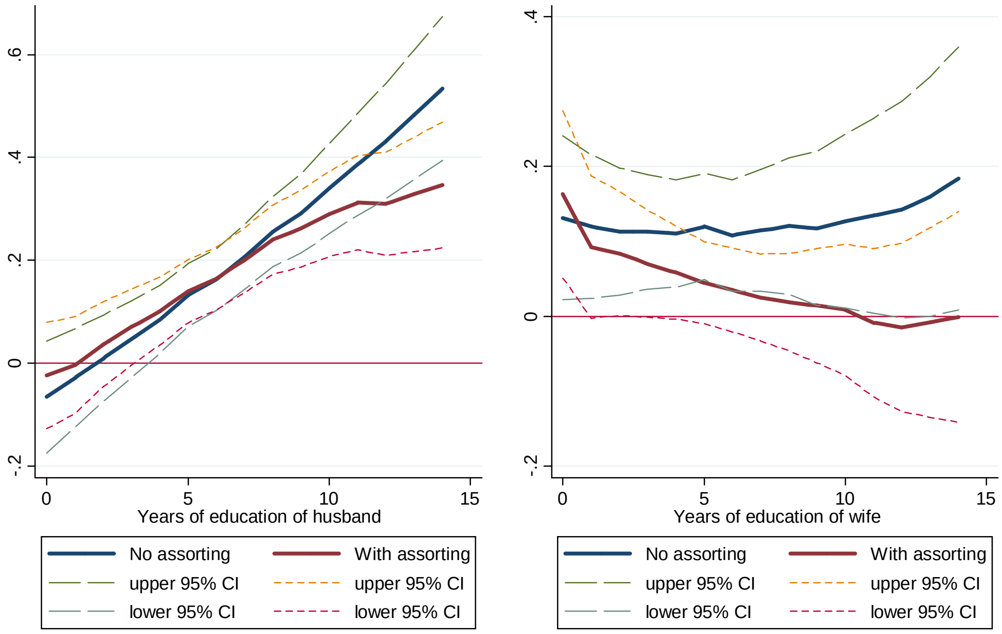
4.2. Further decomposition

We now introduce additional regressors in (4.1) to remove from the PD of parental education factors likely to be driven by general equilibrium effects and by individual heterogeneity. We proceed in two steps: first we include as additional regressors the average levels of male and female education in each parent's cohort; then we further add the educational rank of each parent in their corresponding cohort. We summarize our findings here. Detailed regression results and figures with partial derivatives are available in an online appendix.

We begin by noting that adding the average education of each parent's cohort as regressor has no noticeable effect on partial derivatives with respect to mother and father education. This is best seen from the second horizontal panel of Table 5: we hardly see any difference with the first panel, average PDs are virtually identical. A similar conclusion arises if we plot PDs by education level, as we have done in Figures 1 to 6: the figures are virtually identical too – and hence are not shown here to save space. This suggests that whatever drives PD estimates, it is not the correlation between the education level of individual parents and that of other parents in the same age cohort and birth district. It is therefore unlikely that the correlation between parental education and household outcomes is simply due to general equilibrium effects.

It is, however, conceivable that part of the correlation is due to unobserved heterogeneity in ability and family background. To investigate this possibility, we reestimate the outcome regressions with the educational rank of each parent as additional regressors. Average PDs presented in the third horizontal panel of Table 5 indicate a dramatic change. This is particularly noticeable for the PD of child survival with respect to mother education, which becomes much smaller. But a similar shrinking of PDs is

Figure 7: Partial Derivatives of daughter survival rate
Controlling for rank

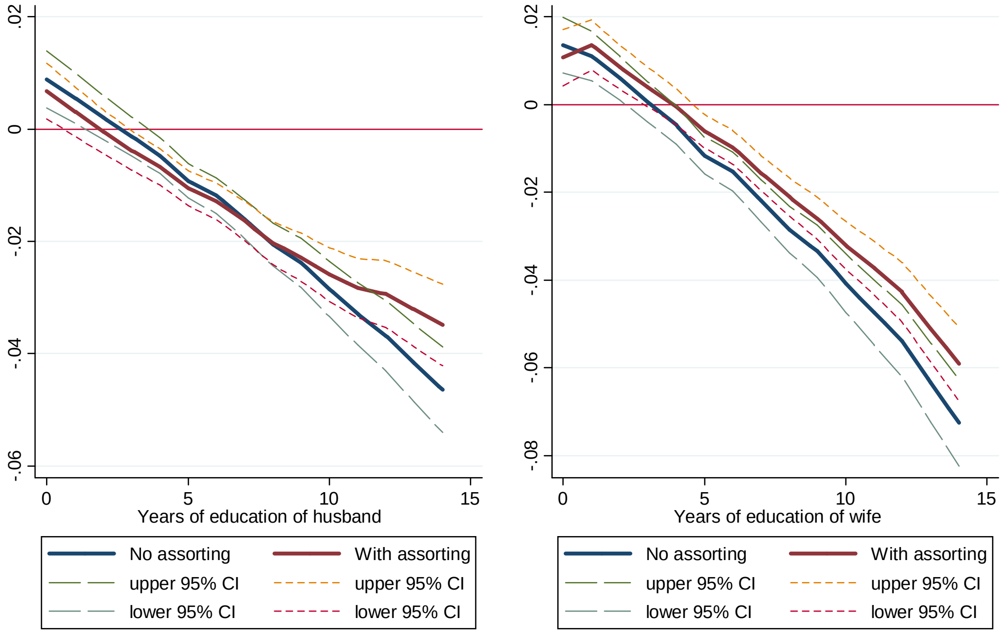


observed for most dependent variables in the Table. Some PDs even change sign, such as the PDs of mother education for the number of sons and daughters among young cohorts of mothers.

To investigate these changes in detail, we reproduce Figures 1 to 6 controlling for average cohort education and education rank. Figure 7 presents the partial derivatives of daughter survival and corresponds to Figure 1. We note a dramatic transformation, especially for female education: unconditional PDs $g_f^u(f)$ are lower across the range while conditional PDs $g_f^c(f)$ are no longer statistically different from 0 at all education levels above 0. Similar results obtain for son survival. It follows that much of the predictive power of female education on child survival disappears once we control for the education rank of the mother in her cohort, and account for the fact that better educated women marry more educated men. Similar findings are obtained in the cubic regression.

In Figure 8 we do the same for the total number of sons. PDs for male and female education are now similar, that is, marginally positive at low levels of education and negative at high levels. This is different from Figure 2 where PDs of female education was everywhere negative. Positive PDs, however, disappear once we include cubic terms in parental education, and so should not be taken too seriously. We obtain

Figure 8: Partial Derivatives of number of sons
Controlling for rank



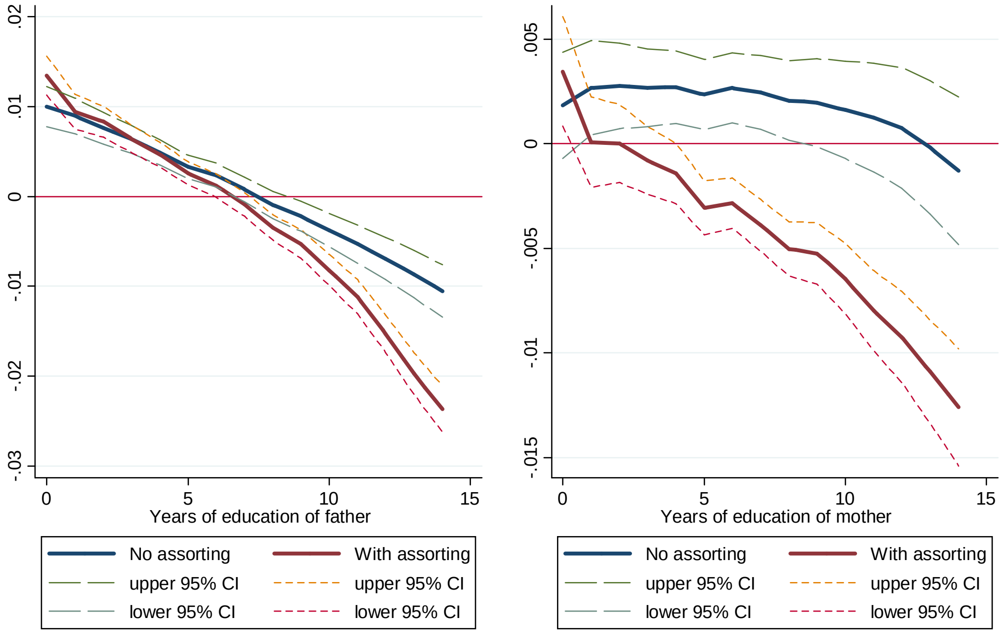
similar results for the number of daughters. We have seen that mother education is on average correlated with having fewer children. If the education rank of mothers in their respective cohort adequately proxies for individual ability and family background,[20] these findings suggest that a large proportion of this correlation may be driven by differences in ability and family background, not by education itself. Figure 8 suggests that the partial derivative of fertility with respect to father and mother education only becomes negative for education levels above primary. This is consistent with the idea it is keeping girls in school at puberty that delays motherhood.

For live birth in the year preceding the census, we find little change in partial derivatives: they are positive for married women with secondary education and above (even more so in the cubic regression), and negative for married men with secondary education. The Figure is omitted to save space.

PDs for school attendance are shows in Figure 9. If we compare with Figure 4, results are striking: PDs are in general much smaller in magnitude. Furthermore, when we correct for assortative matching by education level between spouses, PDs for male and female education take a similar shape: zero or

[20] Or rather for the part of ability and family background that is correlated with education. Any unobserved heterogeneity that is not correlated with parental education is subsumed in the error term and does not affect estimated PDs.

Figure 9: Partial Derivatives of child school attendance
Controlling for rank



positive at low levels of education, and negative above primary education. Virtually identical results are obtained in the cubic regression. This suggests that much of the predictive power of female education on child school attendance is due to unobserved heterogeneity and to assortative matching with a better educated husband.

Partial derivatives for a child's years of schooling (conditional on his age and gender) are shown in Figure 10. Here the biggest difference with Figure 5 relates to PDs with respect to father education, which are basically halved across the range. PDs with respect to female education are less affected.

In Figure 11 we show the results for child work. Here too the difference with Figure 6 is noticeable. Once we control for assortative matching by education, we find that parental education above primary is associated with an increase in child work. This is true for both father and mother although, the latter case, the PD is smaller in magnitude and less precisely estimated. Similar results nevertheless obtain in the cubic regression.

Before concluding, we take a closer look at the coefficient estimates of the various control variables included in our last batch of regressions (Table 6). Fathers who rank higher in their cohort in terms of

Figure 10: Partial Derivatives of child years of schooling
Controlling for rank

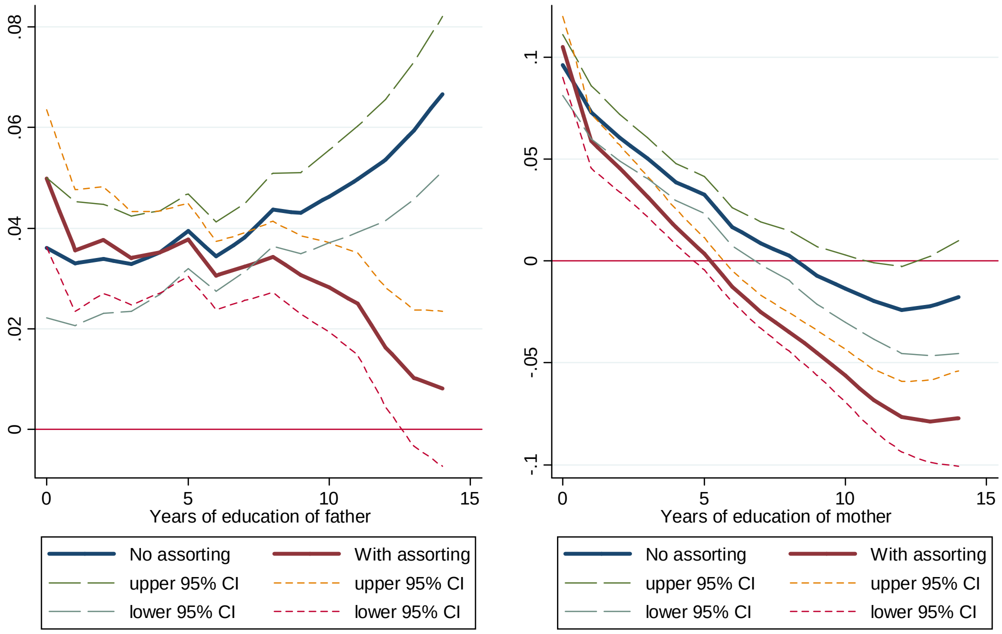
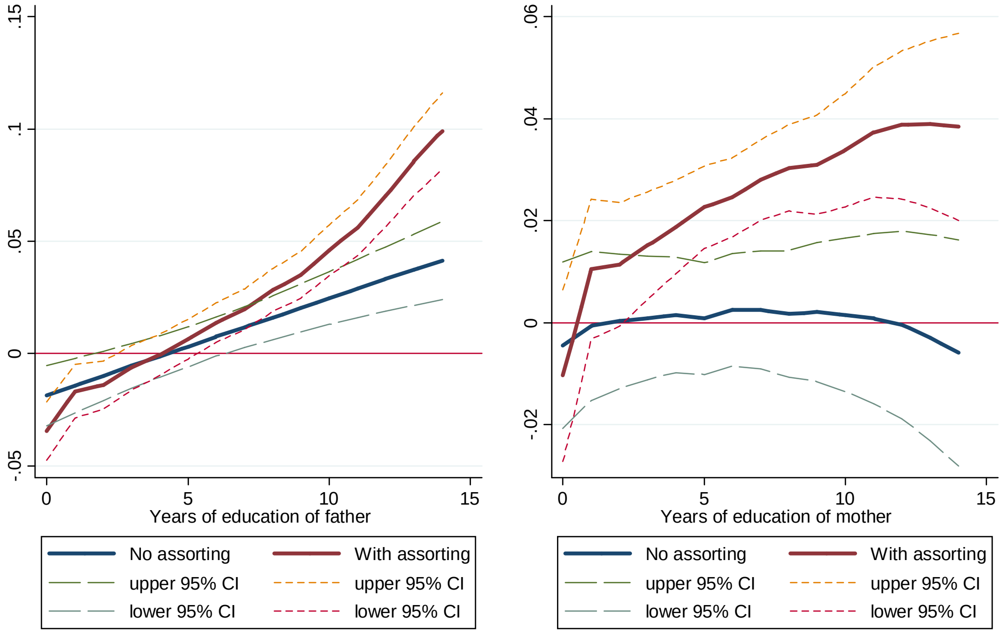


Figure 11: Partial Derivatives of months of child work
Controlling for rank



education are predicted to have more children who attend school more, have more years of schooling, and work less. In contrast, mothers who rank higher in their cohort have fewer sons and daughters and are less likely to have had a child in the year preceding the census. But their children are more likely to survive and go to school, and less likely to work. In the latter case, mother rank has a smaller coefficient than father rank, possibly suggesting a larger role for unobserved father ability and family background in predicting child schooling and child work.

The coefficients of the average education of each parent's cohort are presented next. Cohorts of fathers with a higher average education tend to have fewer children, but these children are more likely to survive and go to school, and less likely to work. Estimated coefficients are consistent across regressions, large in magnitude, and strongly statistically significant. Note the difference in the partial correlation of fertility with average cohort education (which is positive) and the father's educational rank (which is negative). This means that fathers who receive more education than their cohort tend to have more children although cohorts with more educated fathers tend to have fewer children on average. Further, as seen in Figure 8, the PDs of father education are positive at low education levels but negative at high levels. This suggests that the relationship between fertility and the education level of the father is a complex one that is hard to capture adequately in small datasets.

In contrast, the coefficients of the average education of women in the mother's cohort either are non-significant or have an unanticipated sign – i.e., they are associated with higher fertility and lower child welfare. Why this is the case is unclear, but it does not provide much a priori support for the idea that female education generates positive externalities across households.

The last panel of Table 6 reports coefficient estimates for marriage market variables. To recall, cohort gender ratios and education differences are defined such that a higher value captures more bargaining power in the hands of women. An imbalance of the marriage of market in favor of women is generally expected to result in family choices that better reflect the preference of women for fewer, higher quality children (Brien 1997). This is not what we find: controlling for parental education, mothers in a marriage market more advantageous to women have on average more children, a lower child survival rate, less child schooling, and more child work. Why this is the case is unclear, but it could because international work migration affects generate systematic measurement error in our marriage market imbalance measures.[21]

More relevant perhaps are the coefficients of interaction terms between parental education and marriage market conditions. Results show that better educated husbands in cohorts with fewer women tend to have more children who also receive more schooling and work less. In contrast, better educated wives in similar cohorts seem to have fewer children but coefficients are not all significant. Better educated husbands in cohorts where women are relatively more educated tend to have fewer children, and their children are more likely to survive, receive more schooling, and work less. If we think of these husbands as having more bargaining power and thus being able to shape household choices in the direction of their own preferences, this would lead us to infer that their preferences are for fewer high quality children. We find similar albeit less significant coefficients for better educated wives in cohorts where women are more educated. What to make of these results is not entirely clear, but one possibility is that education changes the preferences of both parents in the direction of smaller families of healthier and more educated children.

5. Conclusion

Using data from the 2001 Nepalese population census, we have examined the statistical association between parental education, fertility, and child welfare. This association has received considerable attention in the past, and has been used to advocate promoting female education.

Taking advantage of the large number of observations at our disposal, we study how the partial derivatives of male and female education vary with education. We focus on fertility, child survival, child schooling, and child labor. We find that female education is not as strongly associated with beneficial outcomes as is often assumed, and that male education matters as much if not more. Furthermore, part of the association between female education and household outcomes is driven by marriage market matching with more educated men, and a non-zero cross-derivative between male and female education.

The association between parental education and household outcomes is unaffected if we control for the

[21] Our estimates of marriage market imbalance are based on residents at the time of the census. As a result, districts with more male international migrants appear to have fewer men (and probably less educated men) than they actually had at the time of marriage, and this biases our marriage market imbalance variables. The positive effect of imbalance may be due to unobserved remittance income, which is probably beneficial to household welfare.

average education of each parent's marriage cohort, even though the average education of the cohort is itself a strong predictor of household welfare. This suggests that at least part of the association between education and welfare occurs at household level and is not just driven by an aggregate correlation arising, for example, from general equilibrium, labor market effects, health externalities, or school peer effects.

Unobserved ability and family background may have a direct effect on household welfare that is captured by education. To proxy for these confounds, we use the educational rank of each parent in their respective marriage cohort. The maintained assumption is that better able children who receive more support from their parents receive proportionally more education than others in their cohort. Once we control for the educational rank of the parents, the positive association between female education and beneficial outcomes becomes weaker, disappears, or is reversed. In many cases, partial derivatives for female education become similar to those for male education. For women, the association between educational *rank* and outcomes is very strong, especially for fertility: women who perform better than their peers in school have fewer children and educate them better. In contrast, for men the statistical association between education and household outcomes remains strong even after we control for their educational rank.

These results are closest to those obtained by Behrman and Rozenzweig (2002) who use natural experiment data from a developed economy. Amin and Behrman (2011) also find that cross-section correlations overestimate the effect of mother schooling on fertility. In a recent paper, Muralidharan (2013) reports findings from India suggesting that the majority of children learn very little in primary school. If this is also true in Nepal, maybe it is unrealistic to expect large intergenerational benefits from female education.

We also investigate whether relative parental education interacts with marriage market imbalances. We find that, other things being equal, better educated fathers in marriage markets favorable to women tend to have more beneficial child welfare outcomes in terms of education, child work, and child survival compared to less educated fathers in the same marriage market. The pattern for mothers is weaker and less consistent across regressions.

Partial derivatives can be thought of as marginal treatment effects subject with omitted variable bias.

What, if anything, do they reveal about the possible causal effect of parental education on fertility and child welfare? Here are some tentative suggestions. First, there is so much variation in partial derivatives by education level that underlying marginal effects are unlikely to be constant either. It follows that average treatment effects, which are typically all that can be reliably estimated in small experimental samples, need not be sufficiently informative for policy.

Secondly, treatment effects observed at the level of an individual need not scale up to the whole population due to a fallacy of composition. This was illustrated, for partial derivatives, by the difference between estimates with and without correction for assortative matching. This is a general problem, though: treatment effects estimated from small scale experiments are informative about the likely effect of an intervention of the same scale, but not necessarily about a scaled-up intervention. The results presented here illustrate how partial derivatives may provide some indication about the possible magnitude of the difference, thereby helping assess the external validity of experimental results.

Third, treatment effects may result from an individual response to treatment, or be mediated by labor market effects, externalities, peer effects, or any other aggregate feedback effect. Experimental evidence often cannot distinguish between individual and aggregate effects. Even in experiments designed to estimate peer effects, the scale of the intervention is often limited, so it is unclear how much larger aggregate feedback effects would be if the intervention were scaled up.[22] Here too partial derivatives estimated from observational data may provide an order of magnitude.

Fourth, self-selection into treatment is always a potential concern for estimation. We have sought to reduce the omitted variable bias in partial derivatives by introducing a proxy for unobserved heterogeneity. We do not claim to have entirely eliminated the potential bias. The educational rank of the mother and father in their respective birth cohort may under-control for unobserved heterogeneity. It may also over-control for education, that is, absorb variation in education that has a truly causal effect on fertility and child welfare.[23] In this case, estimates of partial derivatives obtained with the proxy can be thought of

[22] This is because the magnitude of the aggregate multiplier depends on the size and proportion of the treated population in ways that are difficult to estimate from experimental results.

[23] This can arise for instance because of variation in school supply within district. In this case part of the variation in educational rank is driven by the exogenous variation in school supply within district, and thus rank captures part of the exogenous variation of interest that is not due to unobserved heterogeneity. Other examples include idiosyncratic shocks that force some children out of school.

Because primary schools are mixed-gender, the over-control effect should in principle affect mother and father in more or as lower bounds on the causal effect of parental education.

Taken together, the results presented here confirm earlier findings and suggest that we may need to revisit the respective roles of male and female education in reducing fertility and promoting child welfare. This is important at a time when, in many countries, women are now acquiring more education than men (World Bank 2012a, 1012b)[24] and when many men fall behind in terms of earnings. If the results presented here are confirmed elsewhere, the time may have come to shift the emphasis on keeping boys in school *as well as* girls.

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less the same way. Since father education remains a strong predictor of child welfare after we control for rank while mother education less so, it is unlikely that over-control accounts for our findings. It is, however, possible to construct arguments to the contrary. For instance, parents may be more likely to pull a girl out of school as a result of a shock, so that there is more exogenous variation in girl education resulting from shocks, and hence the educational rank of the mother absorbs more of the exogenous variation in education. Similarly, distance to school may have a stronger disincentive effect on girl education, e.g., if parents hesitate to send a girl to a distant school but are willing to send a boy. We cannot rule out these possibilities.

[24] Pitt, Rosenzweig and Hassan (2011) show that the educational gap between men and women in Bangladesh is now to the advantage of women. Similar trends have been noted elsewhere. For instance, in the United Kingdom the government reported (BBC Tuesday, 30 January 2007, 15:56 GMT) that 47% of 17-30 year-old women had gone into higher education by 2004, compared to 37% of young men. Based on an opinion poll of 2,400 11 to 16-year-olds, the BBC reported (Monday, 27 August 2007, 23:11 GMT 00:11 UK) that about three-quarters (76%) of girls in the UK want to go to university compared with about two thirds of boys (67%).

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Table 1. Household outcome data					
Household outcome variables	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Son survival rate x 100 (1)	219587	94.14	17.67	0	100
Daugher survival rate x 100 (2)	197492	93.01	18.57	0	100
Number of sons (3)	276102	1.60	1.28	0	12
Number of daughters (3)	276102	1.44	1.38	0	12
Live birth during preceding 12 months (3)	276040	6.4%			
Male months of work	308120	9.40	3.68	0	12
Female months of work	308111	4.57	4.83	0	12
Marriage Market and Education indicators					
Male-Female gender ratio in marriage pool	280345	-0.08	0.10	-0.59	0.39
Difference in average education in marriage pool	280345	-2.29	1.14	-7.31	1.16
Average education of male cohort (1 -- based on husband age)	298947	4.19	2.49	0.04	12.00
Average education of male cohort (2 -- based on wife's age)	285354	4.17	2.54	0.00	12.00
Average education of female cohort (1 -- based on wife's age)	286189	1.89	2.09	0.00	10.79
Average education of female cohort (2 -- based on husband's age)	299276	1.89	2.06	0.00	11.18
Male education rank in cohort	284564	0.52	0.23	0.01	1.00
Female education rank in cohort	284564	0.53	0.18	0.01	1.00
Individual regressors					
Male education	308125	4.01	4.73	0	15
Female education	308125	1.76	3.56	0	15
Male age	308125	39.53	10.27	10	98
Female age	308125	35.03	9.83	12	98
Male mother tongue Nepali	308125	49.8%			
Male hindu	308125	83.0%			
Male brahmin	308125	15.6%			
Male chhetri	308125	16.1%			
Male newar	308125	7.6%			
Female mother tongue Nepali	308125	50.0%			
Female hindu	308125	82.9%			
Female brahmin	308125	15.5%			
Female chhetri	308125	16.1%			
Female newar	308125	7.5%			
(1) Conditional on having at least one son					
(2) Conditional on having at least one daughter					
(3) Conditional on wife between 15 and 49 years of age					

Table 2. Children outcome data						
Child outcomes		**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
	School attendance dummy (1)	410211	76.4%			
	Number of years of education (1)	410310	2.53	2.53	0	10
	Month of work during preceding year (2)	240735	0.97	2.75	0	12
Child specific variables						
	Child age	410310	10.31	2.83	6	15
	Female child dummy	410310	48.0%			
	# older male co-residing siblings	410310	0.72	0.90	0	10
	# older female co-residing siblings	410310	0.60	0.83	0	9
	Biological mother only (dummy)	410310	1.9%			
	Biological father only (dummy)	410310	1.4%			
Household variables						
	Household size	410310	6.29	2.05	3	38
	Number children/Household size	410310	0.53	0.14	0.05	0.82
(1) Only recorded for children aged 6 to 15						
(2) Only recorded for children aged 10 to 15						

Table 3. Household regressions										
	Son survival		Daugher survival		Number of sons		Nber of daughters		Birth in year	
Marriage market variables	coef	t	coef	t	coef	t	coef	t	coef	t
Gender ratio in marriage pool	-0.679	-1.076	-1.077*	-1.708	0.114***	3.097	0.138***	3.618	0.001	0.102
Gender ratio x Demeaned male education	-0.140	-1.347	-0.058	-0.459	0.034***	5.138	0.047***	6.544	0.001	0.864
Gender ratio x Demeaned female education	0.003	0.028	-0.063	-0.492	-0.019**	-2.059	-0.007	-0.828	-0.000	-0.196
Gender difference in average education in marriage pool	-0.430***	-5.852	-0.398***	-4.568	0.041***	7.322	0.039***	7.619	0.003***	2.948
Education difference x Demeaned male education	0.049***	5.203	0.047***	4.801	-0.003***	-4.740	-0.003***	-5.008	0.000	0.799
Education difference x Demeaned female education	0.016	1.418	0.014	1.298	-0.003***	-3.727	-0.002*	-1.841	0.000	0.414
Education and age variables										
Male education	-0.128**	-2.118	-0.196***	-2.907	0.037***	11.017	0.023***	6.427	0.001	1.016
Male education squared	0.020***	5.870	0.023***	5.919	-0.002***	-11.831	-0.002***	-10.879	-0.000**	-2.334
Female education	0.240***	3.483	0.120*	1.766	0.012***	3.174	0.007*	1.736	-0.001	-0.785
Female education squared	-0.010***	-2.581	-0.004	-0.948	-0.002***	-7.665	-0.002***	-5.816	0.000**	2.151
Male education x female education	-0.017***	-4.403	-0.019***	-4.860	0.001***	6.726	0.001***	5.903	0.000	0.019
Male age	-0.082	-1.283	-0.245***	-3.979	0.074***	24.724	0.065***	18.399	-0.004***	-4.276
Male age squared	-0.002	-1.576	0.001	0.771	-0.002***	-18.758	-0.001***	-15.532	0.000***	3.702
Female age	0.013	0.183	0.122*	1.648	0.137***	32.649	0.142***	32.018	-0.011***	-10.604
Female age squared	-0.006***	-2.945	-0.005**	-2.360	-0.003***	-22.132	-0.002***	-19.952	0.000***	5.975
Male age x female age	0.006**	2.108	0.002	0.619	0.002***	11.218	0.002***	8.832	-0.000*	-1.939
Male age x male education	0.005***	3.861	0.006***	4.774	-0.001***	-6.383	-0.000***	-2.838	-0.000	-0.121
Female age x female education	0.006***	3.793	0.008***	4.589	-0.001***	-11.716	-0.001***	-9.488	-0.000	-0.153
Language, religion, and caste dummies										
Male mother tongue is Nepali	-0.363	-0.703	0.133	0.305	0.001	0.049	0.033	1.243	0.002	0.339
Male hindu	-0.460	-0.682	-2.110***	-3.021	0.033	1.028	-0.004	-0.085	-0.014	-1.628
Male brahmin	0.563	0.652	1.362	1.052	-0.114***	-2.639	-0.025	-0.497	0.011	0.946
Male chhetri	-0.736	-1.022	1.123	1.395	-0.029	-0.693	0.026	0.549	0.012	1.252
Male newar	0.048	0.047	0.434	0.437	-0.066	-1.399	-0.035	-0.581	-0.009	-0.723
Female mother tongue is Nepali	0.385	0.771	0.202	0.502	-0.003	-0.099	-0.018	-0.657	-0.003	-0.512
Female hindu	0.106	0.161	1.583**	2.258	-0.036	-1.084	-0.022	-0.452	0.009	1.053
Female brahmin	-0.212	-0.248	-1.283	-0.993	0.091**	2.095	0.031	0.596	-0.010	-0.906
Female chhetri	1.241*	1.688	-0.925	-1.156	0.006	0.149	-0.038	-0.789	-0.012	-1.270
Female newar	0.644	0.639	0.376	0.373	-0.003	-0.057	0.000	0.003	0.008	0.669
VDC fixed effects	yes		yes		yes		yes		yes	
Intercept	96.701***	109.759	98.894***	104.337	-2.843***	-47.974	-2.691***	-44.375	0.429***	33.293
Number of observations	200,062		180,144		251,699		251,699		251,670	

Note: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are clustered by VDC.

Table 4. Child regressions

	School attendance		Years of schooling		Months of work	
Child and household characteristics	coef	t	coef	t	coef	t
Child age 7	0.096***	27.605	0.349***	42.125		
Child age 8	0.141***	34.031	0.832***	60.657		
Child age 9	0.180***	36.639	1.308***	67.582		
Child age 10	0.186***	36.464	1.852***	66.367	-1.160***	-25.515
Child age 11	0.205***	36.506	2.478***	72.198	-1.016***	-24.323
Child age 12	0.188***	35.863	2.969***	67.632	-0.854***	-23.661
Child age 13	0.176***	32.942	3.655***	66.756	-0.701***	-21.758
Child age 14	0.144***	27.062	4.253***	66.654	-0.413***	-15.341
Child age 15	0.070***	11.800	4.682***	57.142		
Female child	-0.086***	-21.702	-0.350***	-19.142	0.139***	5.222
Number of older male co-residing siblings	-0.009***	-7.484	-0.015**	-2.174	0.010	0.947
Number of older female co-residing siblings	0.005***	4.102	0.073***	10.358	-0.101***	-10.297
Log(household size)	-0.018***	-4.816	-0.181***	-8.378	0.136***	4.768
Number children/Household size	-0.141***	-19.473	-1.095***	-28.684	0.797***	12.466
Biological mother only	-0.078***	-13.593	-0.407***	-12.575	0.876***	13.119
Biological father only	-0.075***	-10.475	-0.358***	-8.940	0.627***	9.208
Marriage market variables						
Gender ratio in marriage pool	-0.077***	-5.796	-0.248***	-3.922	0.266**	2.541
Gender ratio x Demeaned male education	0.036***	11.774	0.124***	9.514	-0.109***	-6.453
Gender ratio x Demeaned female education	0.005	1.260	0.043**	2.516	-0.016	-0.968
Gender difference in average education in marriage pool	-0.015***	-7.764	-0.140***	-15.226	0.084***	6.989
Education difference x Demeaned male education	0.004***	19.798	0.015***	13.625	-0.021***	-14.019
Education difference x Demeaned female education	0.001**	2.309	0.005***	3.483	0.002	1.074
Education and age variables						
Male education	0.047***	26.564	-0.008	-1.132	-0.144***	-12.631
Male education squared	-0.001***	-13.529	0.000	0.619	0.004***	8.129
Female education	0.033***	14.454	-0.041**	-2.537	0.015	1.313
Female education squared	-0.001***	-5.563	-0.006***	-9.137	0.001***	2.770
Male education x female education	-0.001***	-11.590	-0.005***	-9.098	0.004***	7.319
Male age	0.001	1.010	-0.037***	-7.852	0.018*	1.760
Male age squared	-0.000	-0.191	0.000*	1.854	-0.000	-0.626
Female age	0.005***	4.314	0.019***	3.477	0.010	0.921
Female age squared	-0.000	-1.640	-0.000***	-3.436	0.000	0.259
Male age x female age	-0.000	-0.055	0.001**	2.404	-0.000	-0.492
Male age x male education	-0.000***	-7.683	0.004***	29.697	-0.000**	-2.301
Female age x female education	-0.000***	-8.885	0.006***	14.894	-0.002***	-6.831
Language, religion, and caste dummies						
Male mother tongue Nepali	0.017	1.455	0.126**	2.550	-0.005	-0.065
Male hindu	0.013	1.117	-0.141***	-2.785	-0.038	-0.364
Male brahmin	0.043***	2.770	0.411***	5.203	-0.426***	-4.652
Male chhetri	0.020	1.516	0.165**	2.314	-0.280**	-2.522
Male newar	0.065***	4.680	0.359***	4.607	-0.240**	-2.451
Female mother tongue Nepali	0.005	0.547	-0.030	-0.695	-0.148*	-1.871
Female hindu	-0.023**	-1.979	0.050	1.002	0.065	0.629
Female brahmin	0.015	0.930	-0.029	-0.363	0.177**	1.965
Female chhetri	0.028**	2.186	0.078	1.100	0.102	0.914
Female newar	-0.021	-1.576	-0.028	-0.382	0.008	0.088
VDC fixed effects	yes		yes		yes	
_cons	0.545***	23.525	1.217***	13.133	0.931***	3.779
Number of observations	373,778		373,856		219,103	

Note: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are clustered by VDC.

Table 5. Average partial derivatives																
Initial model	Son survival		Daugher survival		Number of sons		Nber of daughters		Birth in year		School attendance		Years of schooling		Months of work	
	Male ed.	Fem. Ed.	Male ed.	Fem. Ed.	Male ed.	Fem. Ed.	Male ed.	Fem. Ed.	Male ed.	Fem. Ed.	Male ed.	Fem. Ed.	Male ed.	Fem. Ed.	Male ed.	Fem. Ed.
All parents	**0.092**	**0.308**	**0.093**	**0.272**	**0.002**	**-0.024**	**0.000**	**-0.024**	**0.000**	**-0.001**	**0.018**	**0.013**	**0.101**	**0.133**	**-0.075**	**-0.038**
Young cohorts	**0.052**	**0.267**	**0.044**	**0.220**	**0.007**	**-0.015**	**0.002**	**-0.016**	**0.000**	**-0.001**	**0.020**	**0.015**	**0.074**	**0.093**	**-0.072**	**-0.027**
Old cohorts	**0.125**	**0.347**	**0.135**	**0.322**	**-0.002**	**-0.033**	**-0.002**	**-0.031**	**0.000**	**-0.001**	**0.017**	**0.011**	**0.124**	**0.164**	**-0.077**	**-0.047**
With average education in each parent's cohort																
All parents	**0.090**	**0.301**	**0.091**	**0.267**	**0.003**	**-0.023**	**0.001**	**-0.022**	**0.000**	**-0.001**	**0.018**	**0.013**	**0.102**	**0.137**	**-0.075**	**-0.039**
Young cohorts	**0.049**	**0.258**	**0.042**	**0.212**	**0.008**	**-0.013**	**0.003**	**-0.014**	**0.000**	**-0.001**	**0.020**	**0.015**	**0.076**	**0.099**	**-0.073**	**-0.030**
Old cohorts	**0.126**	**0.340**	**0.134**	**0.318**	**-0.002**	**-0.032**	**-0.001**	**-0.029**	**0.000**	**-0.001**	**0.017**	**0.011**	**0.124**	**0.167**	**-0.077**	**-0.048**
With education rank and with average education in each parent's cohort																
All parents	**0.055**	**0.134**	**0.093**	**0.129**	**-0.007**	**0.004**	**-0.003**	**0.004**	**0.000**	**0.000**	**0.005**	**0.002**	**0.039**	**0.082**	**-0.004**	**-0.003**
Young cohorts	**0.016**	**0.091**	**0.045**	**0.075**	**-0.002**	**0.014**	**-0.001**	**0.012**	**0.000**	**0.000**	**0.007**	**0.005**	**0.015**	**0.044**	**-0.003**	**0.006**
Old cohorts	**0.089**	**0.174**	**0.135**	**0.180**	**-0.011**	**-0.004**	**-0.005**	**-0.003**	**0.000**	**0.000**	**0.004**	**0.000**	**0.060**	**0.111**	**-0.005**	**-0.012**

Table 6. Coefficient estimates for selected regressors																
	Son survival		Daugher survival		Number of sons		Nber of daughters		Birth in year		School attendance		Years of schooling		Months of work	
Education rank of each parent	**coef**	**t**	**coef**	**t**	**coef**	**t**	**coef**	**t**	**coef**	**t**	**coef**	**t**	**coef**	**t**	**coef**	**t**
Male education rank in cohort	0.603	1.050	-0.095	-0.162	0.190***	6.057	0.092**	2.474	-0.009	-1.392	0.227***	20.274	1.108***	19.133	-1.238***	-13.193
Female education rank in cohort	2.397***	5.842	1.898***	4.021	-0.390***	-13.881	-0.391***	-12.405	-0.015***	-2.713	0.152***	15.404	0.771***	13.667	-0.502***	-7.461
Average education in each parent's cohort																
Average education of male cohort (1)	0.232***	2.829	0.323***	3.408	-0.020***	-3.786	-0.032***	-5.546	-0.002	-1.544	0.018***	9.412	0.103***	10.614	-0.084***	-6.348
Average education of male cohort (2)	0.306***	3.688	0.137	1.522	-0.030***	-5.862	-0.025***	-4.805	-0.002*	-1.891	0.007***	4.767	0.058***	7.869	-0.057***	-5.666
Average education of female cohort (1)	-0.042	-0.517	0.014	0.168	-0.008	-1.515	-0.011**	-2.156	0.001	1.414	0.002	1.093	-0.050***	-6.831	0.047***	4.915
Average education of female cohort (2)	-0.172**	-2.316	-0.242***	-3.172	0.015***	3.041	0.013***	2.860	0.000	0.249	-0.008***	-5.369	-0.073***	-8.308	0.025**	2.524
Marriage market variables																
Gender ratio in marriage pool	-0.534	-0.840	-0.929	-1.452	0.075**	2.039	0.093**	2.493	0.001	0.174	-0.088***	-6.540	-0.381***	-5.963	0.344***	3.277
Gender ratio x Demeaned male education	-0.120	-1.144	-0.052	-0.409	0.037***	5.657	0.048***	6.656	0.001	0.690	0.041***	12.820	0.145***	10.486	-0.134***	-8.009
Gender ratio x Demeaned female education	0.025	0.223	-0.043	-0.336	-0.026***	-2.844	-0.013	-1.626	-0.000	-0.239	0.004	0.968	0.035**	2.002	-0.004	-0.223
Education difference x Demeaned male education	0.048***	4.995	0.046***	4.705	-0.003***	-4.993	-0.003***	-5.065	0.000	0.951	0.004***	18.472	0.013***	11.924	-0.019***	-13.380
Education difference x Demeaned female education	0.017	1.475	0.014	1.279	-0.003***	-2.988	-0.001	-1.347	0.000	0.411	0.001***	4.770	0.008***	5.609	-0.002	-1.150
Child and household characteristics											Yes		Yes		Yes	
Education and age variables	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Language, religion, and caste dummies	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
VDC fixed effects	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	

Note: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are clustered by VDC.

(1) cohort centered on own age (2) cohort centered on spouse's age + (husband) or - (wife) 5 years

6. Online Appendix

Table A1. Household regressions with average education in each parent's cohort

	Son survival		Daugher survival		Number of sons		Nber of daughters		Birth in year	
Average education in each parent's cohort	**coef**	**t**	**coef**	**t**	**coef**	**t**	**coef**	**t**	**coef**	**t**
Average education of male cohort (1)	0.203***	2.621	0.333***	3.881	-0.032***	-6.547	-0.039***	-6.837	-0.001	-1.145
Average education of male cohort (2)	0.310***	3.743	0.141	1.565	-0.031***	-6.018	-0.026***	-4.952	-0.002*	-1.926
Average education of female cohort (1)	-0.203***	-2.712	-0.114	-1.450	0.018***	4.065	0.015***	3.336	0.002**	2.567
Average education of female cohort (2)	-0.182**	-2.465	-0.246***	-3.227	0.015***	3.072	0.014***	2.989	0.000	0.325
Marriage market variables										
Gender ratio in marriage pool	-0.506	-0.796	-0.920	-1.436	0.075**	2.023	0.091**	2.408	0.001	0.119
Gender ratio x Demeaned male education	-0.138	-1.325	-0.052	-0.416	0.033***	5.095	0.046***	6.459	0.001	0.859
Gender ratio x Demeaned female education	0.012	0.106	-0.057	-0.440	-0.021**	-2.301	-0.009	-1.099	-0.000	-0.184
Gender difference in average education in marriage pool	subsumed in average education of each cohort									
Education difference x Demeaned male education	0.050***	5.305	0.047***	4.861	-0.003***	-5.085	-0.004***	-5.355	0.000	0.744
Education difference x Demeaned female education	0.016	1.378	0.014	1.290	-0.003***	-3.472	-0.001*	-1.661	0.000	0.495
Education and age variables										
Male education	-0.136**	-2.246	-0.199***	-2.936	0.038***	11.224	0.025***	6.891	0.001	1.074
Male education squared	0.020***	5.871	0.023***	5.913	-0.002***	-11.648	-0.002***	-10.803	-0.000**	-2.325
Female education	0.227***	3.298	0.105	1.544	0.014***	3.784	0.010**	2.419	-0.001	-0.807
Female education squared	-0.010***	-2.583	-0.004	-0.965	-0.002***	-7.773	-0.002***	-5.777	0.000**	2.136
Male education x female education	-0.017***	-4.416	-0.019***	-4.872	0.001***	6.775	0.001***	5.981	0.000	0.019
Male age	-0.080	-1.163	-0.252***	-3.806	0.073***	23.978	0.062***	16.830	-0.004***	-4.518
Male age squared	-0.002	-1.562	0.001	0.910	-0.002***	-18.925	-0.001***	-15.594	0.000***	3.846
Female age	0.038	0.511	0.151*	1.944	0.133***	31.661	0.138***	29.966	-0.011***	-9.889
Female age squared	-0.006***	-3.034	-0.006**	-2.482	-0.003***	-21.824	-0.002***	-19.265	0.000***	5.686
Male age x female age	0.006**	2.118	0.002	0.610	0.002***	11.273	0.002***	8.918	-0.000*	-1.901
Male age x male education	0.005***	4.060	0.007***	4.820	-0.001***	-6.779	-0.000***	-3.530	-0.000	-0.229
Female age x female education	0.006***	3.847	0.008***	4.726	-0.001***	-11.512	-0.001***	-9.749	-0.000	-0.072
Language, religion, and caste dummies										
Male mother tongue is Nepali	-0.368	-0.715	0.130	0.298	0.003	0.097	0.035	1.298	0.002	0.340
Male hindu	-0.464	-0.688	-2.120***	-3.037	0.035	1.080	-0.002	-0.035	-0.014	-1.637
Male brahmin	0.542	0.611	0.894	0.668	-0.050	-1.099	0.077	1.324	0.013	1.073
Male chhetri	-0.733	-0.988	0.873	1.064	0.002	0.053	0.077	1.538	0.013	1.297
Male newar	-0.042	-0.041	0.109	0.108	-0.009	-0.189	0.050	0.801	-0.007	-0.546
Female mother tongue is Nepali	0.382	0.765	0.199	0.495	-0.003	-0.093	-0.018	-0.650	-0.003	-0.516
Female hindu	0.096	0.146	1.581**	2.255	-0.033	-1.008	-0.020	-0.395	0.009	1.068
Female brahmin	-0.680	-0.764	-1.242	-0.921	0.142***	3.192	0.070	1.272	-0.012	-1.036
Female chhetri	0.999	1.307	-0.881	-1.076	0.032	0.734	-0.019	-0.377	-0.013	-1.295
Female newar	0.339	0.339	0.352	0.346	0.032	0.685	0.028	0.494	0.006	0.524
VDC fixed effects	yes		yes		yes		yes		yes	
Intercept	95.759***	97.759	98.050***	94.580	-2.629***	-41.241	-2.423***	-35.720	0.430***	29.236
Number of observations	200,062		180,144		251,699		251,699		251,670	

Note: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are clustered by VDC.

(1) cohort centered on own age (2) cohort centered on spouse's age + (husband) or - (wife) 5 years

Table A2. Child regressions with average education in each parent's cohort

	School attendance		Years of schooling		Months of work	
Average education in each parent's cohort	**coef**	**t**	**coef**	**t**	**coef**	**t**
Average education of male cohort (1)	0.005***	3.181	0.039***	4.266	-0.012	-1.044
Average education of male cohort (2)	0.007***	4.723	0.058***	7.756	-0.056***	-5.556
Average education of female cohort (1)	-0.008***	-5.983	-0.100***	-15.281	0.080***	8.684
Average education of female cohort (2)	-0.009***	-6.287	-0.079***	-8.971	0.029***	3.012
Child and household characteristics						
Child age 7	0.096***	27.626	0.350***	41.817		
Child age 8	0.140***	34.080	0.831***	60.074		
Child age 9	0.179***	36.644	1.307***	67.291		
Child age 10	0.186***	36.532	1.850***	65.896	-1.162***	-25.538
Child age 11	0.205***	36.534	2.475***	71.787	-1.018***	-24.342
Child age 12	0.188***	35.894	2.966***	67.259	-0.855***	-23.681
Child age 13	0.175***	32.990	3.650***	66.353	-0.702***	-21.801
Child age 14	0.144***	27.076	4.248***	66.377	-0.413***	-15.354
Child age 15	0.069***	11.758	4.676***	56.970		
Female child	-0.086***	-21.687	-0.350***	-19.096	0.138***	5.216
# older male co-residing siblings	-0.009***	-7.523	-0.015**	-2.285	0.010	0.950
# older female co-residing siblings	0.005***	3.991	0.071***	9.949	-0.100***	-10.178
Log(household size)	-0.018***	-4.905	-0.186***	-8.661	0.138***	4.859
Number children/Household size	-0.141***	-19.501	-1.097***	-29.141	0.796***	12.483
Biological mother only	-0.078***	-13.557	-0.406***	-12.547	0.875***	13.107
Biological father only	-0.075***	-10.445	-0.355***	-8.839	0.625***	9.182
Marriage market variables						
Gender ratio in marriage pool	-0.084***	-6.240	-0.359***	-5.616	0.317***	3.010
Gender ratio x Demeaned male education	0.035***	11.703	0.118***	8.906	-0.107***	-6.352
Gender ratio x Demeaned female education	0.004	1.200	0.038**	2.234	-0.014	-0.837
Education difference x Demeaned male education	0.004***	19.585	0.015***	13.334	-0.020***	-13.916
Education difference x Demeaned female education	0.001**	2.455	0.005***	3.766	0.002	1.059
Education and age variables						
Male education	0.047***	26.575	-0.002	-0.269	-0.146***	-12.722
Male education squared	-0.001***	-13.547	0.000	0.612	0.004***	8.171
Female education	0.034***	14.816	-0.027*	-1.729	0.006	0.574
Female education squared	-0.001***	-5.591	-0.006***	-9.289	0.001***	2.656
Male education x female education	-0.001***	-11.584	-0.005***	-8.967	0.004***	7.266
Male age	0.001	0.553	-0.037***	-7.410	0.015	1.375
Male age squared	-0.000	-0.167	0.000	1.455	-0.000	-0.306
Female age	0.005***	3.647	0.004	0.710	0.021*	1.753
Female age squared	-0.000	-1.489	-0.000**	-2.430	-0.000	-0.169
Male age x female age	-0.000	-0.014	0.001**	2.415	-0.000	-0.501
Male age x male education	-0.000***	-7.972	0.004***	27.439	-0.000**	-1.997
Female age x female education	-0.000***	-9.116	0.006***	14.621	-0.002***	-6.324
Language, religion, and caste dummies						
Male mother tongue Nepali	0.017	1.446	0.126**	2.518	-0.004	-0.053
Male hindu	0.013	1.118	-0.140***	-2.754	-0.038	-0.365
Male brahmin	0.056***	3.539	0.558***	6.516	-0.520***	-5.161
Male chhetri	0.025*	1.928	0.232***	3.272	-0.330***	-2.909
Male newar	0.077***	5.610	0.501***	5.788	-0.312***	-3.094
Female mother tongue Nepali	0.006	0.577	-0.024	-0.568	-0.151*	-1.916
Female hindu	-0.022*	-1.940	0.056	1.121	0.064	0.613
Female brahmin	0.020	1.201	0.098	1.166	0.156	1.606
Female chhetri	0.031**	2.354	0.136*	1.922	0.101	0.885
Female newar	-0.018	-1.368	0.063	0.789	-0.025	-0.272
VDC fixed effects	yes		yes		yes	
Intercept	0.583***	24.185	1.783***	17.041	0.676**	2.573
Number of observations	373,778		373,856		219,103	

Note: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are clustered by VDC.

(1) cohort centered on own age (2) cohort centered on spouse's age + (husband) or - (wife) 5 years

Table A3. Household regressions with education rank and with average education in each parent's cohort

	Son survival		Daugher survival		Number of sons		Nber of daughters		Birth in year	
Education rank of each parent	**coef**	**t**	**coef**	**t**	**coef**	**t**	**coef**	**t**	**coef**	**t**
Male education rank in cohort	0.603	1.050	-0.095	-0.162	0.190***	6.057	0.092**	2.474	-0.009	-1.392
Female education rank in cohort	2.397***	5.842	1.898***	4.021	-0.390***	-13.881	-0.391***	-12.405	-0.015***	-2.713
Average education in each parent's cohort										
Average education of male cohort (1)	0.232***	2.829	0.323***	3.408	-0.020***	-3.786	-0.032***	-5.546	-0.002	-1.544
Average education of male cohort (2)	0.306***	3.688	0.137	1.522	-0.030***	-5.862	-0.025***	-4.805	-0.002*	-1.891
Average education of female cohort (1)	-0.042	-0.517	0.014	0.168	-0.008	-1.515	-0.011**	-2.156	0.001	1.414
Average education of female cohort (2)	-0.172**	-2.316	-0.242***	-3.172	0.015***	3.041	0.013***	2.860	0.000	0.249
Marriage market variables										
Gender ratio in marriage pool	-0.534	-0.840	-0.929	-1.452	0.075**	2.039	0.093**	2.493	0.001	0.174
Gender ratio x Demeaned male education	-0.120	-1.144	-0.052	-0.409	0.037***	5.657	0.048***	6.656	0.001	0.690
Gender ratio x Demeaned female education	0.025	0.223	-0.043	-0.336	-0.026***	-2.844	-0.013	-1.626	-0.000	-0.239
Education difference x Demeaned male education	0.048***	4.995	0.046***	4.705	-0.003***	-4.993	-0.003***	-5.065	0.000	0.951
Education difference x Demeaned female education	0.017	1.475	0.014	1.279	-0.003***	-2.988	-0.001	-1.347	0.000	0.411
Education and age variables										
Male education	-0.159**	-2.355	-0.184**	-2.481	0.026***	7.223	0.018***	4.407	0.001	1.419
Male education squared	0.018***	5.524	0.021***	5.503	-0.002***	-10.134	-0.002***	-9.403	-0.000**	-2.163
Female education	0.036	0.494	-0.052	-0.684	0.046***	10.539	0.042***	8.650	0.000	0.125
Female education squared	-0.003	-0.936	0.002	0.358	-0.003***	-12.484	-0.003***	-8.950	0.000	1.617
Male education x female education	-0.016***	-4.087	-0.018***	-4.501	0.001***	5.280	0.001***	4.851	-0.000	-0.042
Male age	-0.077	-1.122	-0.249***	-3.753	0.071***	23.498	0.061***	16.629	-0.004***	-4.530
Male age squared	-0.002	-1.554	0.001	0.907	-0.002***	-18.801	-0.001***	-15.518	0.000***	3.835
Female age	0.036	0.477	0.150*	1.927	0.134***	32.194	0.139***	30.424	-0.011***	-9.885
Female age squared	-0.006***	-2.983	-0.006**	-2.451	-0.003***	-21.999	-0.002***	-19.393	0.000***	5.657
Male age x female age	0.006**	2.095	0.002	0.595	0.002***	11.289	0.002***	8.934	-0.000*	-1.886
Male age x male education	0.005***	3.870	0.006***	4.689	-0.001***	-6.484	-0.000***	-3.093	-0.000	-0.110
Female age x female education	0.006***	3.859	0.008***	4.691	-0.001***	-11.718	-0.001***	-9.808	-0.000	-0.210
Language, religion, and caste dummies										
Male mother tongue is Nepali	-0.376	-0.730	0.122	0.280	0.005	0.169	0.037	1.356	0.002	0.344
Male hindu	-0.444	-0.657	-2.105***	-3.019	0.031	0.957	-0.005	-0.110	-0.014*	-1.646
Male brahmin	0.521	0.586	0.876	0.655	-0.047	-1.039	0.080	1.353	0.013	1.075
Male chhetri	-0.730	-0.982	0.876	1.069	0.004	0.099	0.078	1.549	0.013	1.286
Male newar	-0.046	-0.045	0.114	0.113	-0.008	-0.166	0.051	0.804	-0.007	-0.557
Female mother tongue is Nepali	0.384	0.770	0.201	0.501	-0.003	-0.099	-0.018	-0.652	-0.003	-0.516
Female hindu	0.076	0.116	1.567**	2.237	-0.030	-0.913	-0.017	-0.338	0.009	1.077
Female brahmin	-0.657	-0.739	-1.225	-0.909	0.141***	3.175	0.068	1.237	-0.012	-1.040
Female chhetri	1.010	1.320	-0.879	-1.073	0.031	0.698	-0.020	-0.405	-0.013	-1.297
Female newar	0.331	0.330	0.333	0.326	0.035	0.757	0.032	0.552	0.006	0.533
VDC fixed effects	yes		yes		yes		yes		yes	
Intercept	94.047***	89.489	96.994***	90.046	-2.504***	-36.946	-2.248***	-30.470	0.443***	29.369
Number of observations	200,062		180,144		251,699		251,699		251,670	

Note: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are clustered by VDC.

(1) cohort centered on own age (2) cohort centered on spouse's age + (husband) or - (wife) 5 years

Table A4. Child regressions with education rank and with average education in each parent's cohort

	School attendance		Years of schooling		Months of work	
Education rank of each parent	**coef**	**t**	**coef**	**t**	**coef**	**t**
Male education rank in cohort	0.227***	20.274	1.108***	19.133	-1.238***	-13.193
Female education rank in cohort	0.152***	15.404	0.771***	13.667	-0.502***	-7.461
Average education in each parent's cohort						
Average education of male cohort (1)	0.018***	9.412	0.103***	10.614	-0.084***	-6.348
Average education of male cohort (2)	0.007***	4.767	0.058***	7.869	-0.057***	-5.666
Average education of female cohort (1)	0.002	1.093	-0.050***	-6.831	0.047***	4.915
Average education of female cohort (2)	-0.008***	-5.369	-0.073***	-8.308	0.025**	2.524
Child and household characteristics						
Child age 7	0.096***	27.645	0.350***	41.984		
Child age 8	0.141***	34.222	0.831***	60.046		
Child age 9	0.179***	36.762	1.307***	67.300		
Child age 10	0.186***	36.777	1.850***	65.644	-1.166***	-25.513
Child age 11	0.204***	36.569	2.472***	71.503	-1.019***	-24.266
Child age 12	0.188***	35.965	2.964***	66.959	-0.858***	-23.637
Child age 13	0.175***	33.054	3.647***	65.855	-0.703***	-21.845
Child age 14	0.143***	26.945	4.244***	66.041	-0.414***	-15.348
Child age 15	0.068***	11.683	4.671***	56.629		
Female child	-0.086***	-21.721	-0.350***	-19.119	0.138***	5.217
# older male co-residing siblings	-0.009***	-7.449	-0.015**	-2.255	0.009	0.874
# older female co-residing siblings	0.004***	3.632	0.069***	9.578	-0.097***	-9.915
Log(household size)	-0.018***	-4.934	-0.186***	-8.780	0.141***	4.913
Number children/Household size	-0.134***	-18.619	-1.062***	-28.765	0.765***	12.084
Biological mother only	-0.078***	-13.511	-0.406***	-12.685	0.873***	13.203
Biological father only	-0.076***	-10.602	-0.358***	-8.950	0.628***	9.269
Marriage market variables						
Gender ratio in marriage pool	-0.088***	-6.540	-0.381***	-5.963	0.344***	3.277
Gender ratio x Demeaned male education	0.041***	12.820	0.145***	10.486	-0.134***	-8.009
Gender ratio x Demeaned female education	0.004	0.968	0.035**	2.002	-0.004	-0.223
Education difference x Demeaned male education	0.004***	18.472	0.013***	11.924	-0.019***	-13.380
Education difference x Demeaned female education	0.001***	4.770	0.008***	5.609	-0.002	-1.150
Education and age variables						
Male education	0.034***	19.019	-0.065***	-7.389	-0.072***	-6.663
Male education squared	-0.001***	-9.497	0.001***	2.925	0.002***	4.779
Female education	0.023***	10.417	-0.079***	-5.043	0.038***	3.022
Female education squared	-0.000	-1.313	-0.004***	-6.039	-0.000	-0.130
Male education x female education	-0.001***	-11.385	-0.005***	-9.143	0.004***	7.511
Male age	0.001	0.648	-0.037***	-7.281	0.014	1.351
Male age squared	-0.000	-0.025	0.000	1.629	-0.000	-0.382
Female age	0.005***	3.545	0.003	0.615	0.022*	1.822
Female age squared	-0.000	-1.303	-0.000**	-2.215	-0.000	-0.259
Male age x female age	-0.000	-0.120	0.000**	2.310	-0.000	-0.463
Male age x male education	-0.000***	-9.323	0.003***	26.095	-0.000	-0.746
Female age x female education	-0.000***	-8.874	0.006***	15.404	-0.002***	-6.576
Language, religion, and caste dummies						
Male mother tongue Nepali	0.018	1.599	0.132***	2.727	-0.010	-0.146
Male hindu	0.012	1.049	-0.143***	-2.811	-0.034	-0.328
Male brahmin	0.057***	3.634	0.565***	6.679	-0.530***	-5.323
Male chhetri	0.028**	2.122	0.246***	3.398	-0.350***	-3.104
Male newar	0.082***	5.981	0.526***	5.889	-0.336***	-3.272
Female mother tongue Nepali	0.005	0.508	-0.029	-0.675	-0.148*	-1.851
Female hindu	-0.022*	-1.934	0.054	1.081	0.064	0.620
Female brahmin	0.020	1.207	0.099	1.182	0.157	1.629
Female chhetri	0.030**	2.313	0.135*	1.883	0.108	0.955
Female newar	-0.021	-1.569	0.050	0.609	-0.016	-0.162
VDC fixed effects	yes		yes		yes	
Intercept	0.360***	13.766	0.676***	6.290	1.701***	5.923
Number of observations	373,778		373,856		219,103	

Note: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are clustered by VDC.