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An Analysis of Gender and Sibling Rivalry Using Field Survey Data*

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Abstract

This paper aims to identify the obstacles to school progression by integrating field surveys conducted in twenty-five Pakistani villages, using economic theory and econometric analysis. The full-information maximum likelihood (FIML) estimation of the sequential schooling decision model reveals important dynamics of the gender difference in educational attainment, intrahousehold resource-allocation patterns, and transitory income and wealth effects. We find a high educational retention rate and observe that school progression rates between male and female students after secondary school are comparable. In particular, we find gender-specific and schooling-stage-specific birth-order effects on education. Our overall findings are consistent with the theoretical implications of optimal schooling behavior under binding credit constraints and the self-selection in education-friendly households. Finally, we find serious supply-side constraints on primary education for females.

JEL Classification: D91; I21; J24; O15; O53

Keywords: Sequential schooling decisions; Income shocks; Birth-order effects; Supply-side constraints

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1. Introduction

The recent revival of the economic growth theory has generated renewed interest in the nexus between human capital investment and economic growth (Barro and Sala-i-Martin, 2004). Cross-country studies reveal that human capital investments in Pakistan are poor: school enrollment rates are low and there is great gender disparity in education (Behrman and Schneider, 1993; Sawada, 1997). The theory suggests that the low level of schooling in Pakistan may have a strong negative effect on the country's long-term macroeconomic growth.

At the household level, human capital is accumulated through a complicated decision-making process. Educational outcomes typically depend on years of completed schooling, which is a stock rather than a flow variable. Current educational outcomes, therefore, depend not only on current decisions but also on past decisions about children's education. Thus, general reduced-form solutions of the household's educational investment problem should include the entire history of exogenous influences (Strauss and Thomas, 1995). Yet, historical data on individual and household characteristics are rarely available and the dynamic aspects of educational attainments are often ignored in the empirical literature on educational investments. Even if the data required for this theory were available, introducing dynamics whereby the current educational outcome depends on the past outcomes complicates the estimation procedure.

This paper attempts to overcome the problems of inadequate data and static analyses that are found in the existing literature on education. We believe that in doing so, the paper makes two contributions. First, it shares the findings based on a unique data set on the entire retrospective history of child education and household background characteristics in sample households in Punjab and the North-West Frontier Province (NWFP), Pakistan. The data were collected exclusively for this analysis. Second, this paper uses the full-information maximum likelihood (FIML) method to deal with the complicated estimation procedure involving the multiple integration of conditional schooling probabilities. This method, combined with the unique data set, enables us to estimate the full sequential model for understanding household decisions regarding schooling.

In this paper, we attempt to identify the major obstacles to school progression in rural Pakistan. The estimation results for sequential schooling probabilities provide new and important insights on the household demand for education. Four important findings emerge from our estimation. One of our most striking discoveries is the high rate of educational retention, particularly among girls. In fact, male and female students show similar rates of progression at a higher level of schooling. Second, we find gender-specific birth-order effects that suggest the existence of resource competition among siblings. At lower levels of schooling, the school progression of a child is positively associated with the number of older sisters s/he has. At higher levels of schooling, a child's schooling probabilities increase with the number of older brothers. Third, we find that these schooling patterns can be partly explained by household human capital and physical asset ownership as well as by parental income and health shocks. These results are consistent with the theoretical implications of the optimal educational investment behavior under binding credit constraints, suggesting that the lack of sufficient credit availability is the major obstacle to school progression in rural Pakistan. Also, our third finding is consistent with the hypothesis of self-selection of children in education-friendly households, wherein all children are given equal opportunities for higher education. Finally, we find that constraints on the supply of education in villages significantly restrict educational attainment, particularly for girls.

This paper proceeds as follows. In Section 2, we describe the key features of human capital investments in rural Pakistan as revealed by the field research. Based on these field observations, we apply the standard theory of dynamic schooling investment decisions in Section 3. In Section 4, we use this theoretical framework to derive an econometric model for estimating the conditional schooling probabilities, and then present the estimation results. The final section lists conclusions and policy implications.

2. Key Features Identified through Field Observations

Our research approach follows an iterative process suggested by Townsend (1995), which involves the following: (1) initial hypothesis, (2) field survey, (3) theory, and (4) empirical analysis. Instead of directly implementing econometric tests based on existing data, we begin with the key features of household behaviors discovered through our field study. The discovery of these features led us to modify the data collection procedure during the initial stage. We then augmented the standard theory according to the information collected during field study.

The field survey is designed exclusively for this paper. In the first round of the survey, conducted between February and April 1997, the survey team interviewed families in 14 villages of the Faisalabad and Attock districts of the Punjab province. In the second round from December 1997 to January 1998, the team interviewed selected families in 11 villages of the Dir district of the NWFP. The survey covered 203 households in Punjab and 164 households in the NWFP and collected information on 2,365 children in those households.[1] The data provide a complete set of retrospective histories of children's schooling in addition to a wide range of

[1] The selection of our survey sites was predetermined because we essentially resurveyed the panel households that had participated in the interviews for the Food Security Management Project of the International Food Policy Research Institute (IFPRI) (Alderman and Garcia, 1993; Alderman, 1996). The

household- and village-level information.

In our retrospective surveys, we used three different sets of questionnaires (Appendix A). The first questionnaire gathered basic information on children and their school progression since the first marriage of the household head. Respondents were asked to compare each year with the average year in order to obtain detailed information regarding income and health shocks for all the years. The second questionnaire collected data on household background characteristics such as household size, permanent components of household resources, and fluctuations in household assets and income over time. The third questionnaire gathered village-level retrospective information by interviewing local government officials and/or educated village residents such as schoolteachers; for example, one of the questions inquires about when the primary schools for boys and girls were set up in the village.

Our survey uncovered a number of noteworthy features of household behavior. The most striking feature was the high educational retention rate. According to our survey data, the average number of years of schooling was 1.6 for girls and 6.6 for boys. However, *for children who had entered primary school,* the average number of years of schooling was 6.0 for girls and 8.8 for boys. These figures indicate that a substantial proportion of children in rural Pakistan do not receive any education.

In order to examine the rates of school progression at different educational stages, we estimate the conditional survival function, that is, the probability of school continuation. The Pakistani educational system constitutes five years of primary education and five years of secondary education, followed by postsecondary education.[2] Educational outcomes can be

initial IFPRI data collection was based on a stratified random sampling scheme. A detailed description of the procedure for our field surveys is summarized in Appendix A.

[2] In precise terms, secondary education in Pakistan comprises three years of middle school education and

modeled as an outcome of five sequential schooling decisions that households make. We define S_τ as the schooling time of a child at the τ^{th} educational stage. Then, the first decision a household makes is whether to enroll a child in primary school (S_1). For households with children already in primary school, the second decision is whether to keep the children enrolled until they graduate from primary school (S_2). In the third stage, households choose whether to enroll primary school graduates in secondary school or to discontinue education at Grade Five (S_3). Next, the households decide whether to withdraw a child from school before Grade Ten or to continue her/his education until the completion of secondary school (S_4). The final decision is whether to send a child to an institute of higher education (S_5), i.e., college, technical school, or teaching school.[3]

Let n_k denote the number of students who have completed education at stage S_{k-1}. To determine this number, we use data on children for whom S_{k-1} is not right-censored at education level $k - 1$. The set of individuals whose school attainment is at least S_{k-1} is referred to as the risk set at the k^{th} stage of education S_k. Then, n_k represents the size of the risk set at level k. Among n_k students, let h_k be the number of children who have completed education at level k so that $h_k = n_{k+1}$. Then, an empirical estimate of the conditional survival probability at education level k would be h_k/n_k. This ratio represents the fraction of students who progressed to a higher stage of education, conditional on the completion of education level $k - 1$. This can also be interpreted as the conditional sample probability of school continuation to education level k.

The estimated conditional probabilities for educational survival are summarized in Table 1. The survival rate at the first educational entry point—that is, the probability of entering

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two years of secondary school education.

[3] We assume that the decision of not sending a child to primary school was made when the child was 6 years old, which is the median age for primary school entry (Table 3). We impose similar assumptions for

school—is low for both boys (59%) and girls (22%). In the case of girls, the probability of entering primary school is less than half that for boys. However, after entering primary school, the conditional rates of primary school graduation are 78% for boys and 67% for girls. These statistics indicate that a majority of the children remain in school once they enroll. Another interesting finding is that while girls have a lower conditional probability of entering and graduating from primary school and entering secondary school than do boys, in the Punjab province, girls' conditional schooling probabilities after secondary school entry are consistently higher than those of boys.[4] The gender differences in educational attainments eventually disappear at higher levels of schooling. We believe that this finding is new and makes a contribution to the existing literature; further, it is an indication that gender dynamics are more complex than previously recognized (King and Hill, 1993; Schultz, 1995).

We consider two competing hypotheses that might explain these patterns. The first hypothesis is the "pick-the-winner" hypothesis (PTW hypothesis, hereafter), wherein parents select a limited number of children as the winners for educational specialization and allocate more resources to them. The alternative hypothesis is the self-selection in education-friendly households at higher levels of schooling (EFH hypothesis, hereafter), wherein parents try to educate all children equally. In order to compare these two competing hypotheses, we calculate an indicator of child education-friendliness (Education-friendliness index; EFI), which is measured by the proportion of children in the household who have completed each education level. If the EFI for households that send children to school at a certain level is higher than that for households that discontinue children's education, the EFH hypothesis would be verified.

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secondary and postsecondary education.

[4] Table 1 also shows that many girls discontinue education before entering secondary school, whereas many boys drop out of secondary school after enrolling in it.

Table 2 presents the average values of the EFI for each educational stage. These values show, for example, that if one or more children complete primary school in a family, on average, 42.9% of all children in the family will also enter primary school. On the other hand, if no child completes primary education, on average, only 28% of the children in the family enter primary school. If the PTW hypothesis were true, the former figure would be lower than the latter. Our results reveal that children who continued education hailed from education-friendly households.

Further, at the primary school entry level, the EFI of households with one or more daughters who completed primary school is 29.80% (Table 2). The degree of education friendliness is less clear in the case of girls; nonetheless, it should be noted that the EFI is lower in the case of families with no daughter who completed primary school, i.e., 22.94%. Hence, our results are in favor of the EFH hypothesis, not the PTW hypothesis.[5]

Yet, we compare an extreme version of the PTW hypothesis and the EFH hypothesis. If the most capable child is the only one to receive education and the other children in the family are completely ignored, i.e., they receive no education at all, then the average proportion of children who receive education at a certain educational stage should not be correlated with whether or not a child enters the next educational stage. In reality, however, parents observe the learning performance of their children at every educational stage, then pick the best child, and encourage her/him to continue to the next stage. The statistics in Table 2 are consistent with this view although they favor the EFH hypothesis. Moreover, we need to control the effects of child- and household-level characteristics in order to compare these two hypotheses. Therefore, the

[5] Labor economics literature has some acclaimed empirical studies testing this type of selection. For example, Farber and Gibbons (1996) used test scores known to an employee but unknown to her/his employer to test the selection hypothesis. If talented workers are more likely to survive and such talent is correlated with test scores, returns to test scores (talent) should increase over time. Similarly, the survival rate in schooling for children should be high when education friendliness, unobservable to many, is high in our setting.

numbers reported in Table 2 should be interpreted with some reservation.

The basic data also suggest substantial differences in the extent of gender disparity in education at the district level. Table 1 shows that in the Dir district of the NWFP, the conditional survival rates are consistently lower for girls at all stages of schooling decisions. The differences by district appear to be largely due to sociocultural factors. For example, the custom of seclusion of women, *purdah*, is maintained strictly in the Dir district. These regional divergences in the gender disparity in education in rural Pakistan raise an important policy issue.[6]

3. The Standard Theory of Educational Investments

Having discussed the key field observations, we next formulate a formal model of a household's optimal schooling behavior. As an initial theoretical framework, we employ two sets of optimal behavioral rules. First, parents decide on the intertemporal allocation of resources in order to maximize the expected total lifetime utility of the family. Second, they decide the allocation of educational resources among their children, given the overall resource constraints of the household.

We use a human capital investment model under uncertainty, which is similar to the models used by Levhari and Weiss (1974) and Jacoby and Skoufias (1997), as a benchmark and apply it in the context of rural Pakistan. In particular, we extend the Jacoby and Skoufias (1997) model to a more general form with multiple children under risk, uncertainty, and a household's constraints on insurance and credit.

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[6] Alderman et al. (1995) suggested that when the government allocates education expenditures, disadvantaged groups such as girls and children in lagging regions should be targeted in order to ensure more equitable gains from schooling.

Suppose that a household with n children decides on household consumption C and normalized schooling time S_i for child i, with $0 \le S_i \le 1$, in order to maximize its aggregated expected utility with the concave instantaneous utility function $U(\bullet)$, given the information set at the beginning of time t. Such a household's problem can be represented as follows:

$$\underset{\{C_t, S_{it}\}}{Max}\, E_t\left[\sum_{k=0}^{T-t}\left(\frac{1}{1+\rho}\right)^k U(C_{t+k}) + \left(\frac{1}{1+\rho}\right)^{T+1} W(A_{T+1}, H^C_{1T+1}, H^C_{2T+1}, \cdots, H^C_{nT+1})\right]$$

$$s.t. \quad A_{t+1} = \left[A_t + Y_t(H^P) + \sum_{i=1}^{n} w_i(1 - S_{it}) - C_t\right](1 + r_t)$$

$$H^C_{it+1} = H^C_{it} + f(S_{it}, q_{it}) + e_{it}, \quad i = 1,\ 2,\ \cdots,\ n$$

$$A_t + Y_t(H^P) + \sum_{i=1}^{n} w_i(1 - S_{it}) + B_i \ge C_t$$

$$B \ge 0, H^P, A_0 \text{ and } B_0 \text{ are given, } A_T \ge 0.$$

In this problem, the household maximization function includes a concave function $W(\bullet)$ of the financial bequest and salvage value of the final stock of the child's human capital. The parameter ρ represents a subjective discount rate. The first constraint is the household's intertemporal budget constraint. The household's consumable resources in each period comprise assets A; stochastic parental income Y, which is a function of parents' human capital H^P; and total child income $\Sigma_i w_i(1 - S_{it})$, with w_i being the child-specific wage rate that is exogenously given.[7] The time endowment of a child is normalized to unity. The second constraint is the human capital accumulation equation. Human capital production is a concave function, $f(\bullet)$, of S and parameter

[7] We assume that a child's schooling does not change the child wage rate immediately, and accumulated human capital H^C is reflected in the income after the child becomes an adult. In rural Pakistan, the child labor market does not appear to be segmented by the level of schooling; as is well known, this is because the wage rate is not sensitive to education in the rural agricultural areas where we conducted our surveys (Fafchamps and Quisumbing, 1999).

q, which implicitly represents the returns to education and is reflected in the value of W. The parameter, q, can also be interpreted as the efficiency of producing human capital. An additive and independent stochastic element e incorporates shocks that affect children's accumulation of human capital. We assume that e is independently distributed with $E_t(e_{it}) = 0$ for all i. The third constraint represents the potentially binding credit constraint where B is the maximum amount of credit available to a household.

This stochastic programming model has $n + 1$ state variables: physical assets A and child human assets H_{it}^C, where $i = 1, 2, \ldots, n$. While general analytical solutions to this household's investment problem cannot be obtained, we can derive a set of first-order conditions that are necessary for an optimal solution by applying the Kuhn-Tucker conditions to the standard Bellman equation.

There are two different solutions to this problem of lifetime utility maximization. When a household can borrow and save at an exogenously given interest rate, the credit constraint is not binding. In this case, the household determines the optimal schooling behavior for its children to equalize the net marginal rate of transformation of human capital production and the non-stochastic market interest rate; that is,

$$\frac{\partial f / \partial S_{it}}{\partial f / \partial S_{it-1}} = 1 + r_{t-1}, \ \forall \ i. \tag{1}$$

By using the implicit function theorem, equation (1) shows that the optimal level of schooling S_{it} is a function of returns to education, the market interest rate, and the lagged schooling variable, S_{it-1}.[8] If the household's credit constraint is not binding, the schooling decision for one child is not affected by the schooling decisions for other children or by the parental income. In this case, two separability conditions hold: one for consumption and schooling decisions, and the other for intrahousehold schooling allocation.

If the household cannot borrow, it effectively faces an endogenous shadow interest rate, which is represented by the marginal rate of substitution of consumption over time. Under credit market imperfections, the separability condition fails to hold for schooling decisions regarding different children. Further, the separability between consumption and schooling investment decisions ceases to exist. At the optimum, the marginal rate of transformation of educational investments should equal the marginal rate of substitution of household consumption:

$$\frac{\partial f / \partial S_{it}}{\partial f / \partial S_{it-1}} = \left(\frac{1}{1+\rho}\right) E_{t-1}\left[\frac{\partial U / \partial C_t}{\partial U / \partial C_{t-1}}\right], \forall\ i. \tag{2}$$

Then, the optimal level of schooling S_{it} is determined by three sets of additional factors that affect the marginal utility and the endogenous shadow interest rate.[9] First, there will be a competition for educational resources among siblings. For example, in any given household, an increase in one child's schooling time or in the opportunity cost of schooling decreases a sibling's optimal level of schooling.[10] Alternatively, the wage earnings of older siblings will enhance the optimal time allocation for the schooling of younger siblings. The second set of variables represents the ownership of physical and human assets. Finally, an ex post realization of shocks to the parental income will affect the child's schooling. In contrast to households with access to credit, wherein the parental income has no effect on a child's schooling, a credit-constrained household has to contend with high marginal costs of schooling if there is a negative income shock. This reflects the inseparability of consumption and schooling decisions under a binding credit constraint.

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[8] See Appendix B for an analytical solution for this condition under specific functional forms.
[9] See Appendix B for an analytical solution for this condition under specific functional forms.
[10] According to equation (2), the implicit optimization behavior of a household for the i^{th} child is conditional on that for all the other children. The optimal choice of child i's schooling S_i depends on S_{-i}, which is the optimal schooling decision made for a child other than i. This solution can be interpreted as a standard demand system.

Testable Implication I: Gender Difference

There are three testable hypotheses that could be derived from our model. First, it is often argued that in Pakistan, the significant difference between males and females in terms of returns to schooling leads to a distinct gap in educational investments (Fafchamps and Quisumbing, 1999). We utilize our framework's human capital production function, *f*(•), to show that the gender difference in schooling outcomes is the result of a household's optimization behavior. From (1) and (2), it is clear that regardless of credit accessibility, the following relation should hold between the schooling of a male child *i* and a female child *j* in the family:

$$\frac{\partial f / \partial S_{it}}{\partial f / \partial S_{it-1}} = \frac{\partial f / \partial S_{jt}}{\partial f / \partial S_{jt-1}}. \tag{3}$$

In order to illustrate the role of returns to education, we utilize the Jacoby and Skoufias (1997) specification of the education production function:

$$f(S_{it}, q_{it}) = q_{it}\left[\gamma_0 - \gamma_1 \exp\left(-S_{it}\right)\right], \tag{4}$$

where $\gamma_0 > 0$ and $\gamma_1 > 0$. From (3) and (4), the optimal investment rule implies that

$$\left(S_{it} - S_{it-1}\right) - g_{it} = \left(S_{jt} - S_{jt-1}\right) - g_{jt}, \tag{5}$$

where *g* represents the growth rate of *q*. Equation (5) demonstrates that if the growth rate of returns to education is higher for boys than for girls ($g_{it} > g_{jt}$), a household invests more in a male child *i*'s education than in a female child *j*'s education. We can use these findings to interpret the estimated results of the gender variables in our empirical model.

Testable Implication II: Credit Constraints

The second important testable hypothesis, which can be derived by comparing (1) and (2), concerns the role of credit constraints in educational investments. The analytical solution in Appendix B demonstrates that under the binding credit constraint, a child's schooling is affected by variables related to siblings, proxy variables for asset ownership and household human capital, and shocks to household income. However, these factors should have no effect on a child's schooling under the condition of perfect credit availability.

Testable Implication III: PTW versus EFH

The third important testable implication of our theoretical model concerns the PTW and the EFH hypotheses. The former hypothesis holds when we assume a convexity of $W(\bullet)$, while the latter holds when we assume a concavity of $W(\bullet)$. Suppose that $W(\bullet) = W^A(A_{T+1}) + \Pi_i(H^C_{iT+1})^{\alpha_i}$, where α_i is a weighting parameter. In the steady state, where ΔH^C_{iT+1} is the same for all children in the family, we can combine an optimality condition for an internal solution, i.e., $\partial W(\bullet)/\partial H^C_{iT+1} = \partial W(\bullet)/\partial H^C_{jT+1}$, with equation (4) to derive the following condition: $\frac{q_{it}}{\alpha_i}\left[\gamma_0 - \gamma_1 \exp(-S_{it})\right] = \frac{q_{jt}}{\alpha_j}\left[\gamma_0 - \gamma_1 \exp(-S_{jt})\right]$. If $W(\bullet)$ is concave, $\Sigma\, \alpha_i \leq 1$, and the levels of schooling of the various children in the family should not be too different. Moreover, in this case, the availability of household resources should have an equal effect on children's education. This should be consistent with the EFH hypothesis. On the other hand, if $W(\bullet)$ is convex, a household would attach a greater weight to a particular child, leading to an unequal distribution of educational investments among the children in the family. Assuming that weights are assigned according to each child's ability, this case represents the PTW hypothesis.

Based on the PTW hypothesis, educated parents do not necessarily ensure that all their children progress to higher levels of education. Therefore, the correlation between parental resources and child-level progression in education is supposed to be weak. On the other hand, education-friendly households ensure that all their children move on to higher levels of education; thus, the correlation between parental resources and the rate of child-level school progression becomes positive.

4. The Econometric Framework and Estimation Results

Two empirical approaches for investigating the process of household decision-making with regard to schooling based on the investment model are represented implicitly by equations (1) and (2).[11] The traditional approach employs a linear regression model for years of schooling, with controls for various household background characteristics (Taubman, 1989). The problem with this approach is that it estimates time-invariant parameters for a sequential decision-making process for educational investment. The parameters in this model cannot be interpreted as educational-stage-specific parameters.

A second approach formalizes the process of schooling in a stochastic decision-making model (Mare, 1980; Lillard and Willis, 1994; Behrman et al., 2000). This approach explicitly investigates the determinants of the process of grade transition. The model estimates the

[11] A third approach involves applying the structural estimation framework to a dynamic stochastic discrete choice model. For a literature survey, see Amemiya (1996) and Eckstein and Wolpin (1989). Yet, the schooling choice set of a household with n children comprises 2^n mutually exclusive, discrete dependent variables. Since n averages to approximately seven in the Pakistani households we surveyed, the structural estimation of such a model will be computationally intractable. Applications of this framework to development issues include estimates of fertility decisions using Malaysian data (Wolpin, 1984), sequential farm labor decisions using data from Burkina Faso (Fafchamps, 1993), bullock accumulation decisions of Indian farmers (Rosenzweig and Wolpin, 1993), the gender- and age-specific values of

probability of schooling at the τ^{th} grade conditional on the completion of the $\tau - 1^{th}$ grade. The advantage of this methodology over the linear regression approach is that it can estimate the stage-specific parameters. Amemiya (1975) provides the statistical foundation for estimating such sequential decision-making models. Various scholars applied this approach to estimate the probabilities of school and grade transition. For example, using a Malaysian data set, Lillard and Willis (1994) estimated a model of sequential schooling decision, controlling for individual unobserved heterogeneity. Cameron and Heckman (1998) constructed a theoretical model to examine the effect of household characteristics on school transition probabilities. Other papers focused on only one transition from among many sequences of the schooling process, such as the transition probability of high school graduates (Willis and Rosen, 1979).

We follow the second econometric approach and estimate the sequential schooling decision model jointly. We employ the FIML method that allows for the correlation of error terms in different educational stages and thus mitigates the self-selection bias of education-friendly households.

There are three levels of schooling in Pakistan: primary, secondary, and postsecondary. Children's educational outcomes are assumed to be a result of the five sequential decisions made by the households they live in (Section 2). In order to formalize the sequential schooling process, we define an indicator variable of schooling:

$$\delta_{i\tau} = 1 \text{ if } S_{i\tau} > 0 \qquad (6)$$
$$= 0 \text{ otherwise,}$$

where τ indicates the τ^{th} stage of education and S is a latent variable implicitly corresponding to the variable S in (1) and (2). $\delta_{i\tau} = 1$ if child i enters school at the τ^{th} stage of education. Then, the

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Korean children (Ahn, 1995), and well investment decisions in India (Fafchamps and Pender, 1997).

sequential process of the schooling decision can be described as follows: children are born with zero years of schooling. At the age of 6, some enter primary school, while others remain uneducated. The uneducated children who have *not* entered primary school, $S_{i1} = 0$, are represented by the indicator variable $\delta_{i1} = 0$. Having entered primary school ($S_{i1} > 0$ and $\delta_{i1} = 1$), some children complete this stage of education ($\delta_{i2} = 1$ or $S_{i2} > 0$), while others drop out ($\delta_{i2} = 0$ or $S_{i2} \leq 0$). After graduating from primary school, some children enter secondary school ($\delta_{i3} = 1$ or $S_{i3} > 0$), while others do not ($\delta_{i3} = 0$ or $S_{i3} \leq 0$). Then, some children proceed to complete secondary school ($\delta_{i4} = 1$ or $S_{i4} > 0$), and others discontinue schooling during this stage ($\delta_{i4} = 0$ or $S_{i4} \leq 0$). Finally, after finishing secondary school, some children enter postsecondary school ($\delta_{i5} = 1$ or $S_{i5} > 0$), while others do not ($\delta_{i5} = 0$ or $S_{i5} \leq 0$).

In the linearized form, equation (2) can be represented as

$$S_{i\tau} = X_{i\tau}\beta_{\tau} + u_{i\tau}\,, \tag{7}$$

where $\tau = 1, 2,\ldots,5$; $u_{i\tau} \equiv S_{i\tau-1} + \varepsilon_{i\tau}$; and $S_{i0} = 0$ by construction. In Appendix B, we derive an analytical solution for $S_{i\tau}$ under specific function forms. While we do not use this explicit structure of the error term, we allow the error terms, $u_{i\tau}$, to be serially correlated. The set of explanatory variables X includes variables on gender and sibling composition, household asset and human capital, and household shock variables.

Assuming that household decision-making is independent across stages of education or, equivalently, $u_{i\tau}$ is independent across τ, the sequential model of equations (6) and (7) can be estimated by maximizing the likelihood functions of dichotomous models (independent error term specification) (Amemiya, 1975). However, our theoretical results in (1) and (2) demonstrate that schooling decisions are not independent across stages and $u_{i\tau}$'s are serially correlated because $u_{i\tau} \equiv X_{i\tau-1}\,\beta_{\tau-1} + u_{i\tau-1} + \varepsilon_{i\tau}$. These serial correlations can be explained, for example, by some unobserved propensity for schooling that is stronger among children who graduated from a certain grade than among those who failed to finish this grade.

Suppose that the joint probability density function of the error term $u_{i\tau}$ is represented by $f(u_{i1}, u_{i2}, u_{i3}, u_{i4}, u_{i5})$. Then, the probability of entering postsecondary education, $Pr\ (\delta_{i5} = 1)$, can be represented by

$$Pr\ (S_{i5} > 0, S_{i4} > 0, S_{i3} > 0, S_{i2} > 0, S_{i1} > 0) \tag{8}$$

$$= \int_{-X_{i1}\beta_1}^{\infty} \int_{-X_{i2}\beta_2}^{\infty} \int_{-X_{i3}\beta_3}^{\infty} \int_{-X_{i4}\beta_4}^{\infty} \int_{-X_{i5}\beta_5}^{\infty} f(u_1, u_2, u_3, u_4, u_5)\, du_5 du_4 du_3 du_2 du_1 \,.$$

The direct calculation of such a high-dimensional integral is computationally complex and may be unfeasible because the integral must be evaluated at each step of the likelihood maximization. Two possible methods can be used to deal with this problem. Both methods rely on the fact that the unconditional joint distribution (8) can be presented as a weighted sum of the products of univariate distributions. If no assumptions are made regarding the form of the joint distribution of the error terms in the system of equations represented by (7), $u_{i\tau}$, then, assuming the common-factor error structure, the joint distribution can be approximated nonparametrically by a step function (Heckman and Singer, 1984; Mroz, 1999). Alternatively, under the assumption of joint normality, the distribution of the error terms in the system of equations represented by (7) can be approximated using the Gauss-Hermite quadrature (see Judd, 1998). Although the first method imposes fewer restrictions on the error structure in the system of equations represented by (7), it is computationally less stable. The likelihood function that results from a nonparametric estimation of the error distribution (8) is highly nonlinear, and our maximization algorithm fails to find a global optimum. An approach based on the Gauss-Hermite quadrature demonstrates better convergence properties, and this is the method we use for our estimations. (We refer to this method as the FIML method.) Then, the log-likelihood function $\Im$ for the system of equations represented by (7) is as follows:

$$\Im = \sum_{n=1}^{N} Log\left\langle \sum_{m_1=1}^{M_1} \omega_1 \sum_{m2=1}^{M_2} \omega_2 \sum_{m3=1}^{M_3} \omega_3 \left[\prod_{\tau=1}^{5} PR^{\tau}\left(X_{i\tau}\beta_{\tau} \mid \upsilon_{m_1}, \upsilon_{m_2}, \upsilon_{m_3} \right) \right] \right\rangle, \tag{9}$$

where N is the total number of observations in the sample, $PR^{\tau}(\bullet)$ is the set of the cumulative distribution functions for every equation in system (7) conditional on the common factors, the υ's and ω's are one-dimensional quadrature points (nodes) and weights from a Gauss-Hermite rule (Stroud and Secrest, 1966), and the M's represent the number of quadrature points.[12] As was the case previously, X's represent the equation-specific sets of explanatory variables and β's represent the vectors of unknown parameters that are to be estimated.

The estimations presented in this paper are based on the approximation of the probability integral by the Gauss-Hermite quadrature with three nodes.[13] An additional increase in the number of nodes fails to improve the value of the log-likelihood function. Identification is achieved through the inclusion of stage-specific variables such as school supply, a household's human and physical assets, and income and health shocks. This will be discussed further in the next subsection. According to the likelihood-ratio test criterion, the independent error specification is rejected in favor of the FIML specification that assumes a joint normality of the

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[12] The optimal number of common factors is determined according to the following rule: consider $Q < 0$; $Q = 0.5[(p - m)^2 - p - m]$, where p is the number of equations and m is the number of common factors (Anderson and Rubin, 1956). We require at least three common factors to satisfy this condition in the case of five equations ($p = 5$).

[13] The parameters of the model are estimated by maximum likelihood using the DFP algorithm (Powell, 1977) with analytical derivatives. The variance-covariance matrix of the estimated coefficients is estimated by approximating the asymptotic covariance matrix by the so-called "sandwich" estimator (see, for example, Davidson and MacKinnon, 1993).

error distribution.[14]

4.1. Variables

In estimating the sequential schooling model discussed above, we begin by inspecting the basic characteristics of our data set. The median age of school entry is 6 years for primary school, 11 years for secondary school, and 17 years for postsecondary school (Table 3). On average, children spend 5 years in primary and 6 years in secondary school. Since the formal length of secondary-level schooling in Pakistan is 5 years, an extra year in secondary education indicates grade repetition or a delay in secondary school entry, which is a common occurrence in Pakistani villages.

Table 4 summarizes the descriptive statistics of variables used in the sequential model of equations (6) and (7), in terms of the discrete dependent variable for $S_{i\tau}$ and the covariates of conditional probabilities X. Our independent variables could be divided into six main blocks.

The first block of controls includes variables on gender differences, which are divided into two subgroups according to province. The first gender variable is for the Punjab province. It is a dummy variable that takes 1 for females and 0 otherwise. Similarly, the second gender dummy variable for the NWFP takes 1 for females and 0 otherwise. These dummy variables indicate that the share of female students declined at the primary school entry level (Table 4). Later, we also include the auxiliary gender variable for males in the NWFP, which takes 1 for males in the NWFP and 0 otherwise.

[14] The results of the independent error term specification can be obtained from the authors on request. While the independent error term model is believed to provide biased coefficients owing to the correlations of sequential decisions, the qualitative results of the independent error model and the FIML

In the second block of explanatory variables, we include the number of older brothers and sisters. We could incorporate more detailed sibling composition variables separated by the current schooling status. Yet, an inclusion of such variables will generate serious endogeneity bias. Alternatively, the number of older siblings is predetermined, and therefore, we treat this figure as being exogenous. The descriptive statistics show a negative correlation between the education level of a child and the number of older siblings (Table 4). This suggests that students who could gain access to higher education were from households with a small number of children. This could be reflective of intrahousehold competition for resources between the siblings or of birth-order effects.

The third set comprises household physical and human asset variables and includes the amount of land owned and a dummy variable for tractor ownership.[15] The household human capital characteristics with regard to parental education are represented by dummy variables. These variables take 1 if either of the parents has completed at least primary school, and 0 otherwise. Table 4 shows that children at higher levels of schooling are most likely to be from relatively rich households and to have better-educated parents.

The fourth set of variables, associated with transitory income shocks, includes good or bad year dummy variables based on the household's retrospective assessment of agricultural production, wage earnings, and livestock incomes. The effects of health shocks are also controlled for by the dummy variables that take 1 if the head and/or his spouse are physically inactive and 0 otherwise. Jacoby and Skoufias (1997) emphasize the importance of a distinction between the unanticipated and anticipated components of transitory income movements. Health

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estimates are comparable.

[15] Although our theory requires the inclusion of asset accumulation as an independent variable, we utilize a total asset variable instead of its first difference. This is simply because in rural Pakistan, the markets

shocks could be interpreted as unanticipated components because they are largely unexpected. Income movements, on the other hand, might include both anticipated and unanticipated components.

The fifth block of control variables contains gender-specific school supply variables. The first supply dummy takes 1 if a child is a boy and if there is a boys' school in his village. The second supply dummy variable takes 1 if the child is a girl and her village has a girls' school. At the primary school entry level, 34% of boys and only 19% of girls face no supply constraints for schooling (Table 4).[16]

The final block comprises a household's social class or caste status. Traditionally, caste status, called *biraderi* in Punjab and *quam* in the NWFP, has been defined based on occupational position (Eglar, 1960; Ahmad, 1977; Barth, 1981; Ahmed, 1980). For example, landless agricultural laborers are strictly distinguished from landowners. Nonagricultural laborers, such as casual laborers and artisans, are also differentiated from landowners. This caste system has prevailed in the form of social norms, and members of each caste are expected to act according to their social and economic status. The caste system indirectly constrains the educational opportunities of lower-caste children. In order to capture these sociocultural effects, we include dummy variables for parents' occupation—farmers with land, landless farmers or nonfarm casual laborers, and business and government officials. The categories that are excluded are unemployed and/or those who stay home due to illness. Table 4 shows that in the initial stage of schooling, about 44% of children hail from landless households. At higher schooling stages, the percentage of children of landless farmers or casual laborers declines significantly.

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for land and agricultural machinery are few; therefore, we do not frequently observe change in assets.

[16] No village in our sample has upper-secondary and/or postsecondary education. This implies that supply constraints such as the accessibility of schools are severe at higher levels of schooling.

Consequently, the share of the children of landowners increases after primary school graduation. These casual findings are consistent with the sociocultural background of Pakistani society.

The average age of children in our sample was 20.5 years in 1998 (Table 4). However, there is a large variation in age. Some of those sampled are older than 50 years. The age distribution indicates that there will be a potentially large cohort effect, which the empirical model needs to control for. Hence, we include age cohort dummy variables.

4.2. Estimation Results of the Sequential Schooling Decision Model

Table 5 summarizes the results of the estimation of the full sequential schooling decision model at each school level. These results are derived from FIML estimations of conditional probabilities represented by equations (8) and (9). Detailed descriptions and interpretations of our FIML estimation results are presented below.

Gender Effects

The coefficients on gender dummies indicate that girls have lower conditional schooling probabilities at the primary school entry and school completion levels than do boys (Table 5). This may reflect the different trends in returns to education by gender. The absolute levels of coefficients on the dummies for females in the Punjab province are smaller than those in the NWFP at the level of primary school entry, indicating a smaller gender gap in education in Punjab. These regional differences reflect the different degrees of sociocultural gender constraints in the two regions. Yet, after secondary school entry, the coefficients on the female dummies are not statistically significant in either region. The gender differences in education appear to vanish among students studying at secondary and postsecondary levels in Punjab and the NWFP. Therefore, school progression rates between male and female students become comparable at higher levels of schooling. In fact, we found positive (although statistically insignificant) coefficients on female dummies at higher levels of schooling in Punjab.

Table 6 summarizes the simulated marginal changes in schooling probabilities with respect to gender dummy variables, evaluated at the means of the dependent variables.[17] The marginal effects differ for girls and boys at the primary school entry level, and the difference disappears on completion of secondary school. For example, other things equal, for girls, the probability of entering primary school is 37% lower than that for boys living in Punjab and 43% lower than that for boys living in the NWFP. However, the probability of secondary school graduation is almost identical for boys and girls living in both provinces. We also investigated the effects of the interaction terms between the gender and the household variables. As Table 7 shows, none of the estimated coefficients are statistically significant, suggesting that girl-child education friendliness is not necessarily captured by landownership or income shocks.

Development researchers and practitioners have argued that in Pakistan, women are significantly less educated than men are (Khan, 1993; Shah, 1986; Chaudhary and Chaudhary, 1989; Behrman and Schneider, 1993). There are several possible explanations for the gender differences in education. For example, the high opportunity costs of girls' education in rural Pakistan may lead to intrahousehold discrimination against women in terms of education.

[17] These marginal effects are based on the estimation results reported in Table 5. To calculate the marginal effects in a given simulation, a certain value of the interest variable is assigned to all the households in the sample in a particular state. The simulated probabilities are generated for each household by integrating the estimated distribution and averaging the probabilities across the sample. Next, the value of the interest variable is changed, and this changed value is assigned to the entire sample of households. Then, a new set of simulated probabilities is generated. The marginal effect, that is, the effect of the changes in the particular parameter on the probabilities of school participation, is calculated as the difference in these simulated probabilities.

Parents might have a negative perception toward girl-child education due to the custom of *purdah*.

In summary, the results of our estimations indicate that gender differences in Pakistani education are schooling-stage-specific. Although there are distinct gender differences in primary-level education, the gap is likely to disappear when children begin secondary-level education. These findings suggest that education policies for girls should target the primary level.

Sibling Competition

According to the estimated coefficients on the sibling variables in Table 5, the number of older sisters appears to be positively associated with the higher probability of primary and secondary school entry for younger siblings. Greenhalgh (1985) and Parish and Willis (1993) arrived at similar conclusions after analyzing the gender differences in education in Taiwan. Elder daughters may extend the household's resource availability, either by marrying early or by serving as a source of domestic labor in the house. In addition, since elder daughters naturally have fewer older sisters, the probability of elder daughters completing primary and secondary education is lower. This suggests that households do not discriminate against all daughters; elder daughters might bear a large share of the burden under binding resource constraints (Strauss and Thomas, 1995).

On the other hand, at the secondary school completion and postsecondary entry levels, having more elder brothers increases the schooling probability of a child. This suggests that the education of the younger siblings at the secondary and postsecondary levels is supported partly by the contribution of elder brothers to household resources. At these higher levels of schooling, elder sons' monetary contributions to household resources might be more important than elder daughters' nonmarket domestic labor contribution.

Existing empirical studies demonstrate mixed results for birth-order effects—that is, the effects of sibling resource competition over time.[18] There is no consensus in the literature on whether birth-order effects really exist, and if they do exist, on whether the effects are positive, negative, or nonlinear in form (Parish and Willis, 1993). Our results suggest that, under credit constraints, birth-order effects exist, and more importantly, these effects are specific to gender and education levels.[19]

Household Physical Assets

At the decision point for primary school entry, the tractor ownership variable has a positive and significant coefficient (Table 5). In impoverished Pakistani villages, tractor ownership is an obvious measure of a household's wealth. Hence, our results suggest that the probability of entering primary school is systematically higher for children hailing from wealthy households. Moreover, it has been argued that technology and education complement each other

[18] There are two possible outcomes (Behrman and Taubman, 1986). The first possibility is a negative birth-order effect on education. With the birth of more children, the household's resource constraints become severe and fewer resources are available per child. If this per child resource shrinkage effect is dominant, the younger (higher birth-order) siblings will receive lesser education than older siblings do. Alternatively, there can be a positive birth-order effect on education. The effect of resource competition effects might decline over time since households can accumulate assets and increase income over time. Moreover, the older children may enter the labor market, contributing to household resources. Therefore, younger (higher-order) siblings could spend more years at school. Moreover, since siblings can share various educational inputs and materials, there might exist an economy of scale due to household-level public goods. Positive knowledge externalities might be important as well since younger children can learn easily from the experience of their older siblings through homeschooling. In summary, if resource extension effects, scale economies, and externalities are larger than competition effects, the presence of older siblings might promote rather than impede the education of a younger child.

[19] There has been progress in the literature on gender-specific birth-order effects. For example, see Rosenzweig and Wolpin (2000) and Butcher and Case (1994). Further, it is important to note that in the context of Pakistani villages, Fafchamps and Quisumbing (2003) found that Pakistani households operate as hierarchies with sexually segregated spheres of activities, which leads to gender-specific birth-order

(Psacharopoulos and Woodhall, 1985; Foster and Rosenzweig, 1996). It is likely that tractor operation requires at least a basic level of schooling. At the postsecondary education entry level, the landownership variable has positive and statistically significant coefficients on conditional schooling probability. At this level, household ownership of physical assets appears to play an important role in educational decision-making.[20]

Parental Human Assets

In Table 5, variables reflecting parental education have consistently positive and significant coefficients at all primary and secondary levels of schooling. These estimation results demonstrate important complementarities between parental education and investment in children's schooling. Most likely, these complementarities exist because better-educated parents have positive incentives for educating children, improved technical or allocative efficiency in agricultural production, and/or superior homeschooling environments (e.g., Schultz, 1964; Welch, 1970; Behrman et al., 2000). Subjective factors associated with parental human assets might also be important. As Table 8 shows, in 13.4% of the cases, households listed "achieved the desired level" as the primary reason for their children discontinuing school. This is a purely subjective reason, implying that schooling choice may differ depending on ethnicity, network, and social status (Psacharopoulos and Woodhall, 1985). Better-educated parents appear to be more capable of perceiving the benefit of education than uneducated parents since they can estimate the returns to education more precisely.

These findings are consistent with the abovementioned EFH hypothesis and not with the

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effects.

[20] In general, households' resource availability extends their self-insurance ability and thus encourages high-risk and high-return investment opportunities, such as higher education. Risk-taking and

PTW hypothesis. Educated parents value education in general and therefore try to invest more in all their children, regardless of gender, thus equalizing future incomes among children. Accordingly, the correlation between parental education and the child-level school progression rate becomes positive. This finding is also consistent with a number of empirical studies reporting that parental education influences a child's schooling, such as Behrman and Rosenzweig (2002), Black et al. (2003), Plug (2004), Sacerdote (2002), and Solon (1999). Yet, unlike these studies, we found that parental contribution to a child's schooling is education-stage-specific and differs depending on the level of schooling: As can be seen from Tables 5 and 7, father's education influences primary school entry, but school progression after primary school entry is more influenced by mother's education.

Household Shock Variables

Households in rural Pakistan face considerable income instabilities. As is evident from Table 5, negative income shocks discourage the continuation of schooling at the primary school completion and secondary school entry and completion levels. Moreover, negative health shocks increase the rate of secondary school dropouts. The risk of a large income shortfall, sickness, and the sudden death of an adult member is likely to impose serious constraints on a household's resource allocation because the availability of formal and/or informal insurance and credit is severely limited in rural areas. Therefore, exogenous negative shocks have non-negligible effects on a household's educational investment decisions. Pakistani households might be using child labor income as an insurance against parental income shocks, thereby sacrificing their children's

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precautionary saving behaviors may be closely related to physical asset ownership (Morduch, 1990).

human capital accumulation.[21]

Other Control Variables

Other factors, such as social status and supply of education, might also affect household schooling decisions. Our results show that the school availability coefficients are positive and significant for girls' schools but statistically insignificant for boys' schools. This suggests that the lack of primary and secondary schools in rural areas impedes the education of female students, while supply-side constraints do not affect the educational attainments of male students. The marginal effect of primary school availability in the village of residence is shown in Table 9. Access to a primary school in a village appears to contribute to an 18% increase in the probability of a girl entering primary school. Moreover, the percentage of female primary school dropouts declines by 6%. In fact, our qualitative survey data show that, in 40.3% of school termination decisions in the case of girls, households listed the supply-side constraints as the principal reason for their decision against further schooling (Table 8). Hence, a significant proportion of the gender differences in Pakistani education may be explained by supply-side quantity and quality constraints (Alderman et al., 1995, 1996). The lack of schools affects female education more seriously than it does male education because traditional Pakistani culture requires single-sex schools (Shah, 1986). Parents are unwilling to send their daughters to school if there is no girls' school nearby. Since the risk of violating the *purdah* increases when girls cross a major road or a river on the way to school, parents refuse to send their daughters to schools located outside the village. These sociocultural factors exacerbate the negative effects of constraints in school supply. Moreover, sociocultural forces create the need for female teachers.

[21] Sawada (1997) and Alderman and Gertler (1997) also found that shocks have an important impact on

It has been observed that irrespective of monetary or nonmonetary incentives, girls attend schools only if female teachers are present (Chaudhary and Chaudhary, 1989).[22] Even if there is a girls' school in the village, the chronic shortage of female teachers imposes serious constraints on girls' education. Yet, we should also acknowledge the possibility that the availability of girls' schools could be a reflection of demand factors.

In the case of the final control variable—social class—the estimated coefficients indicate that at the primary and postsecondary entry levels, the children of business or government officials have the highest schooling probabilities. The second finding is that at the primary school entry level, farmers who own land have higher levels of educational investments than landless farmers or casual laborers do. These results suggest that occupation, which is traditionally a reflection of social status, affects educational investment decisions at the initial entry point and at higher levels of schooling.

5. Conclusions and Policy Implications

In this paper, we investigate the sequential educational investment process of Pakistani households by integrating field observations, economic theory, and econometric analysis. We believe that this paper makes two contributions to the literature. First, our analysis is based on

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school enrollment in rural Pakistan.

[22] Although the supply of teachers is partly constrained by the shortage of women candidates, the rural environment also prevents an increase in the number of female teachers in villages. Attracting and retaining high-quality female teachers from outside the villages pose a different set of problems because these teachers must relocate, gain local acceptance, and overcome the obstacle of finding suitable accommodation. There might be chronic absenteeism among locally recruited teachers as well due to domestic responsibilities (Khan, 1993). Nevertheless, monetary compensation to attract women to the teaching profession remains inadequate. Provincial governments, for instance, give teachers in villages lower house rent allowances than they do teachers in urban areas. Moreover, there might be a quality problem with the schools, originating from teachers' low educational levels (Warwick and Jatoi, 1994).

the unique data set on the entire retrospective history of child education and household background characteristics for villages in two regions of Pakistan. The data for this study were collected exclusively through field surveys. Second, we employed the FIML method to deal with the complicated estimation procedure of the multiple integration of conditional schooling probabilities. This method, combined with the unique data set, enabled us to estimate the full sequential model of schooling decisions.

One of the most striking aspects of rural Pakistani education revealed through the data collected is the high educational retention rate of girls. Our analysis demonstrates the important dynamics of the gender difference in education and the significance of shock variables, wealth effects, and intrahousehold resource allocation for educational decision-making. These findings are consistent with a household's optimal educational investment under a binding credit constraint. Hence, a possible policy recommendation is to relax the credit constraints that households face, perhaps through a scholarship program or interest-free student loans for female education. For example, micro-finance programs might indirectly enhance educational investments. Moreover, our results are in favor of the EFH hypothesis, and not the PTW hypothesis, at higher education levels.

In general, however, it is difficult for the government to directly control the demand for education. Hence, while it is possible that the lack of schools is demand-driven, supply-side interventions become critical. The results of our estimations suggest that in addition to household demand considerations, increasing the supply of girls' primary schools might have a substantial positive impact on educational achievements in Pakistan. Indeed, the drive to improve access to schooling by increasing the supply of schools has dominated the education agenda in developing countries since the 1960s (Lockheed et al., 1991). Yet, remote and inappropriate locations for girls' schools and the resultant high costs of schooling still constitute serious problems in rural Pakistan. Therefore, the cost-effectiveness of providing primary education can be improved by directing the allocation of funds to recurring expenditures for the construction of girls' schools and the employment of more female teachers. These supply-side policy interventions have the potential to significantly reduce gender biases in human capital investment in Pakistan.

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Appendix A: A Summary of the Field Survey

Field surveys were conducted on two occasions to gather information exclusively for this paper. In the first round of the survey from February to April 1997, the survey team conducted interviews in fourteen villages of the Faisalabad and Attock districts of the Punjab province. Our selection of survey sites was predetermined, since we resurveyed the panel households that had previously been interviewed by the International Food Policy Research Institute (IFPRI) as part of the Food Security Management Project, based on a stratified random sampling scheme (Alderman and Garcia, 1993). Faisalabad, the first district in our sample, is a well-developed, irrigated, wheat-producing and livestock-raising area. Attock, the second district, is a rainfed, wheat-producing region near the industrial city of Taxila. In this district, earnings from nonfarm activities constitute the major component of household income. The second round surveys were conducted in eleven villages of the Dir district of the North-West Frontier Province (NWFP) from December 1997 to January 1998. Dir, too, is a rainfed, wheat-producing area; it also engages in the production of some cash crops, such as citrus fruits. There is a limited set of nonfarm income-earning opportunities within and around the district. Temporary emigration to countries in the Persian Gulf is common in Dir. The IFPRI data files reveal that as a result of this, nonfarm income and remittances account for more than 60% of the average household income.

In our retrospective surveys, we used three different sets of questionnaires. The first questionnaire comprises questions on basic child information and retrospective school progression. The second questionnaire collects basic household background information, such as household size, permanent components of household resources, and temporal fluctuations in household assets and income. Through the third questionnaire, we gathered village-level retrospective information by interviewing local government officials and/or educated village dwellers such as schoolteachers. In particular, we collected information about the year when boys' and girls' primary schools were set up in the village.

These questionnaires seemed to work effectively in the field. Farmers recollected incidents related to child education and enjoyed talking about their children. Each household interview lasted approximately one-and-a-half to two hours, largely depending on the number of children. Our field surveys covered 203 households in Punjab and 164 households in the NWFP. Thus, 367 households were interviewed, and information on a total of 2,365 children was collected. The combined data set presents a complete set of retrospective histories regarding children's schooling behavior, along with household- and village-level information, which enable the estimation of a full sequential schooling decision model. Moreover, the field survey data set is matched with the IFPRI data files. Since our purpose is an estimation of the full sequential schooling decision model, we use a part of the IFPRI data files that contains long-term retrospective information on household and village characteristics.

Appendix B: An Analytical Solution of the Model

We can derive an analytical solution of the model as presented in equations (1) and (2) if we specify the functional forms of the utility and human capital production functions. For the utility function, we assume the constant absolute risk aversion (CARA) specification.

(A1) $$U(C_t) = \bar{\alpha} - \frac{1}{\alpha}\exp(-\alpha C_t).$$

Note that α represents the coefficient of absolute risk aversion. For the human capital production function, we follow Jacoby and Skoufias (1997) and select the exponential function:

(A2) $$f(S_{it}, q_{it}) = q_{it}\left[\gamma_0 - \gamma_1 \exp(-S_{it})\right],$$

where $\gamma_0 > 0$ and $\gamma_1 > 0$ and it is easily verified that $f_S > 0$ and $f_{SS} < 0$.

Given that parental human capital affects permanent income, let $Y_t^P(H^P)$ and Y_t^T represent the permanent and transitory components, respectively, of parents' income, $Y_t(H^P)$. Then, by definition, we have $Y_t(H^P) = Y_t^P(H^P) + Y_t^T$ with $E_t(Y_t) = Y_t^P(H^P)$ and $E_t(Y_t^T) = 0$. Our next assumption is represented by $Y_t \sim N(Y_t^P(H^P), \sigma_t^2)$—that is, parental income follows an augmented *i.i.d.* normal stationary process. Moreover, we select the following specification for the permanent income function: $Y_t^P(H^P) = \theta H^P t + h(H^P)$, where the first term in the right-hand side represents the human capital adjusted time trend of income with parameter θ. The second term, $h(\bullet)$, is a general nonlinear function that defines the form of parents' human-capital-specific wage profile.

There are two different solutions for this problem. First, when a household can borrow and save money freely at an exogenously given interest rate, the credit constraint is not binding. In this case, the household decides on the optimal schooling behavior so as to equalize the net marginal rate of the transformation of human capital production and the non-stochastic market interest rate. Using the functional form of equation (A2), the optimal schooling decision rule then becomes approximately

(A3) $$S_{it} = X_{it}\beta^N + S_{it-1},\ \forall\ i,$$

where $X\beta^N$ is defined as

(A4) $$X_{it}\beta^N \equiv g_{it} - r_{t-1}.$$

Here, g represents the growth rate of q, which implicitly represents the returns to education, and X is a matrix of proxy variables for g and r. Equation (A3) is a linear difference equation for the optimal schooling decision, S. This equation indicates that the optimal level of schooling is a function of school availability and quality, gender-specific elements, and the market interest rate.

Alternatively, if the household is constrained from borrowing, the optimal condition becomes the equalization of the marginal rate of transformation to the marginal rate of substitution, as shown in equation (2). Under the functional forms of equations (A1) and (A2), the reduced form schooling decision can be represented by the following linear difference equation:

(A5) $$S_{it} = X_{it}\beta^C + S_{it-1} + \varepsilon_{it},\ \forall\ i,$$

where $X\beta^C$ is defined as

$$\text{(A6)}\quad X_{it}\beta^{C} \equiv \underbrace{\left(\frac{g_{it}-\ln\beta}{1+\alpha}\right)}_{\substack{\text{(I)}\\ \textit{Returns to Education}\\ \textit{Subjective Factors}}} - \underbrace{\frac{\alpha}{1+\alpha}\left(\sum_{j\neq i} w_j \Delta S_{jt}^{*}\right)}_{\substack{\text{(II)}\\ \textit{Opportunity Costs of}\\ \textit{Siblings' Schooling}}} + \underbrace{\frac{\alpha}{1+\alpha}(\theta H^{P}+\Delta A_t)}_{\substack{\text{(III)}\\ \textit{Ownership and Accumulation}\\ \textit{of Assets}}} + \underbrace{\frac{\alpha}{1+\alpha}\Delta Y_t^{T}}_{\substack{\text{(IV)}\\ \textit{Ex Post}\\ \textit{Transitory Income}}} - \underbrace{\frac{\alpha^{2}}{2(1+\alpha)}\sigma_t^{2}}_{\substack{\text{(V)}\\ \textit{Ex Ante}\\ \textit{Income Instability}\\ \text{(Precautionary Saving)}}}\ .$$

Note that ε_{it} indicates a mean zero expectation error of parental income Y_t. We allow the possibility of serial correlation for this expectation error. There are four components of the matrix X. First (I), X includes the trend in returns to education and household-specific subjective factors. The second component (II) of X indicates educational resource competition among siblings. For example, an increase in other children's schooling time, ΔS_{jt}, $\forall\, j \neq i$, or opportunity costs, $w_j\Delta S_{jt}$, decreases child i's optimal level of schooling. Alternatively, the wage earnings of older siblings will enhance the optimal time allocation to schooling by decreasing $w_j\Delta S_{jt}$. The third term (III) is the ownership and accumulation of human and physical assets. The fourth component (IV) shows that an ex post realization of the transitory income of parents, ΔY_t^{T}, has a positive impact on a child's schooling. The final term (V) shows the negative effect of income instability. This term essentially indicates that given a positive third derivative of the utility function, there is a motive for precautionary saving as ex ante optimal behavior against income instabilities. The positive precautionary saving negatively affects child education since there is resource competition between asset accumulation and investment in education.

An important testable hypothesis can be derived by comparing equation (A6) and equation (A4). We can easily note that the four terms on the right-hand side of equation (A6)—terms (II), (III), (IV), and (V)—should be 0 under perfect credit availability. On the other hand, under the binding credit constraint, proxy variables for asset ownership and accumulation, transitory income, income stability, and sibling variables should affect a child's schooling behavior. Hence, our theoretical framework offers testable restrictions that characterize two different credit regimes.

Table 1
Sample Probability of School Continuation

		Total		**Faisalabad**		**Attock**		**Dir**	
		Male	Female	Male	Female	Male	Female	Male	Female
Entered primary school	h_1/n_1	0.59	0.22	0.59	0.33	0.62	0.32	0.58	0.15
Primary school graduate	h_2/n_2	0.78	0.67	0.67	0.72	0.82	0.67	0.81	0.63
Entered secondary school	h_3/n_3	0.91	0.48	0.96	0.33	0.85	0.54	0.92	0.56
Secondary school graduate	h_4/n_4	0.80	0.89	0.68	0.93	0.79	0.90	0.85	0.85
Entered postsecondary school	h_5/n_5	0.57	0.57	0.55	0.77	0.39	0.56	0.64	0.48
Sample size	n_1	853	857	199	184	181	172	473	501

Table 2
Education-Friendliness Index (EFI):
Percentage of Children at Each Education Level
for Each Household
(Average of the Relevant Sample)

Education level (τ)	Households that send at least one child to the τ+1 level	Households that send no child to the τ+1 level	Households that send at least one daughter to the τ+1 level (percentage of daughters that progress to the τ+1 level)	Households that send no daughter to the τ+1 level (percentage of daughters that do not progress to the τ+1 level)
Primary school entry	42.90%	28.43%	29.80%	22.94%
Primary school completion	35.12%	24.86%	20.51%	20.51%
Secondary school entry	29.85%	23.67%	13.65%	0%
Secondary school completion	30.71%	18.75%	15.10%	5.83%

Table 3
Distribution of Age at School Entry

	Entire sample			Girls only		
	Primary school	**Secondary school**	**Postsecondary school**	**Primary school**	**Secondary school**	**Postsecondary school**
Percentile						
Youngest 10%	5	10	16	4	10	15
25%	6	11	16	6	11	16
Median	6	11	17	6	11	17
75%	7	12	18	7	12	18
90%	8	13	20	8	13	21
Mean age (standard deviation)	6.43 (1.74)	11.64 (1.73)	17.23 (2.54)	6.22 (1.50)	11.19 (1.42)	17.31 (2.32)
Number of observations	1,150	685	177	335	115	26

Table 4 Descriptive Statistics: Means of Variables

	Primary school entry	Primary school completion	Secondary school entry	Secondary school completion	Postsecondary school entry
	S_1	S_2	S_3	S_4	S_5
Dependent variable					
Dummy variable = 1 if $S_\tau^* = 1$; 0 if $S_\tau^* = 0$, where $\tau = 1, 2, \ldots,$	0.41	0.75	0.81	0.82	0.57
Gender and region variables					
Dummy variable = 1 if Punjab (default)	0.43	0.5	0.49	0.45	0.42
	[765]	[347]	[253]	[188]	[143]
Dummy variable = 1 if the NWFP	0.57	0.50	0.51	0.55	0.58
	[945]	[346]	[265]	[229]	[197]
Dummy variable = 1 if female in Punjab	0.21	0.17	0.15	0.08	0.09
	[359]	[118]	[78]	[33]	[31]
Dummy variable = 1 if female in the NWFP	0.29	0.11	0.09	0.06	0.07
	[496]	[76]	[47]	[25]	[24]
Sibling variables					
Number of older brothers	1.84	1.77	1.68	1.67	1.67
	(1.87)	(1.83)	(1.59)	(1.58)	(1.56)
Number of older sisters	1.57	1.58	1.53	1.53	1.50
	(1.70)	(1.68)	(1.60)	(1.60)	(1.55)
Household's physical and human assets					
Amount of land owned	13.41	17.13	17.81	21.66	22.31
	(37.54)	(46.38)	(44.98)	(50.40)	(53.85)
Dummy variable = 1 if household owns tractor	0.02	0.03	0.04	0.06	0.06
Dummy variable = 1 if the father has finished primary school	0.18	0.30	0.33	0.33	0.36
Dummy variable = 1 if the mother has finished primary school	0.02	0.05	0.06	0.07	0.08
Household's shock variables					
Dummy variable = 1 if it is a good year	0.07	0.05	0.02	0.12	0.06
Dummy variable = 1 if it is a bad year	0.07	0.06	0.02	0.11	0.06
Dummy variable = 1 if the household head has a health problem	0.06	0.06	0.00	0.08	0.02
Dummy variable = 1 if the wife of the household head has a health problem	0.06	0.05	0.01	0.09	0.04
School supply variables					
Dummy variable = 1 if male and the village has a boys' school	0.34	0.61	0.22		
Dummy variable = 1 if female and the village has a girls' school	0.19	0.21	0.03		
Social class variables					
Retired, unemployed, or other (default category)	0.10	0.06	0.08	0.09	0.10
Dummy variable = 1 if the household head runs a business or is an officer	0.16	0.24	0.25	0.24	0.26
Dummy variable = 1 if the household head is a landowning farmer	0.30	0.37	0.36	0.39	0.37
Dummy variable = 1 if the household head is a landless farmer or casual laborer	0.44	0.33	0.31	0.28	0.27
Cohort variables					
Dummy variable = 1 if above the age of 40	0.11	0.09	0.09	0.10	0.10
Dummy variable = 1 if aged between 35 and 40	0.09	0.10	0.10	0.11	0.12
Dummy variable = 1 if aged between 30 and 35	0.12	0.15	0.16	0.17	0.16
Dummy variable = 1 if aged between 25 and 30	0.15	0.19	0.21	0.21	0.21
Dummy variable = 1 if aged between 20 and 25	0.17	0.24	0.25	0.25	0.26
Dummy variable = 1 if aged between 15 and 20	0.12	0.17	0.15	default: 0.16	default: 0.15
Dummy variable = 1 if aged between 10 and 15	0.07	default: 0.06	default: 0.04		
Dummy variable = 1 if below the age of 10	default: 0.17				
Number of observations	1710	693	518	417	340

Numbers in parentheses are the standard deviations. Numbers in square brackets are the sample size of observations.

Table 5
FIML Estimation Results of the Sequential Schooling Decision Model

	Primary school entry		Primary school completion		Secondary school entry		Secondary school completion		Postsecondary school entry	
	S_1		S_2		S_3		S_4		S_5	
	Coeff.	Std. error	Coeff.	Std. error	Coeff.	Std. error	Coeff.	Std. error	Coeff.	Std. error
Gender and region variables										
Dummy variable = 1 child living in the NWFP	–0.036	(0.111)	0.390	(0.141)**	0.367	(0.212)**	0.630	(0.294)**	0.532	(0.238)*
Dummy variable = 1 if female living in Punjab	–1.585	(0.358)***	-1.712	(0.594)***	–2.784	(0.501)***	0.605	(0.469)	0.286	(0.228)
Dummy variable = 1 if female living in the NWFP	–1.927	(0.409)***	-1.629	(0.611)**	–1.926	(0.556)***	–0.428	(0.474)	-0.884	(0.616)
Sibling variables										
Number of older brothers	2.351	(2.716)	2.744	(6.092)	6.820	(7.141)	16.300	(6.146)***	21.017	(8.613)**
Number of older sisters	5.020	(3.041)*	-1.130	(6.670)	14.698	(8.123)*	2.178	(5.889)	3.410	(8.656)
Household's physical and human assets										
Amount of land owned	–2.270	(1.456)	-1.289	(2.220)	4.862	(4.397)	1.403	(2.617)	8.315	(4.501)*
Dummy variable = 1 if household owns tractor	1.454	(0.568)***	-0.040	(0.560)	0.761	(0.611)	#		1.044	(0.588)*
Dummy variable = 1 if the father has finished primary school	1.001	(0.223)***	0.758	(0.301)**	0.600	(0.313)*	0.103	(0.263)	0.220	(0.322)
Dummy variable = 1 if the mother has finished primary school	0.917	(0.390)**	1.253	(0.542)**	2.180	(0.722)***	0.451	(0.455)	0.733	(0.552)
Household's shock variables										
Dummy variable = 1 if it is a good year	–0.289	(0.340)	-0.540	(0.568)	–0.151	(0.772)	–0.147	(0.329)	0.072	(0.534)
Dummy variable = 1 if it is a bad year	0.122	(0.355)	-1.462	(0.589)**	–1.675	(0.781)**	–0.633	(0.307)**	0.199	(0.509)
Dummy variable = 1 if the household head has a health problem	0.169	(0.384)	-0.551	(0.529)	#		–1.113	(0.377)***	#	
Dummy variable = 1 if the wife of the household head has a health problem	0.097	(0.346)	-0.437	(0.603)	#		–0.503	(0.366)	-0.543	(0.581)
School supply variables										
Dummy variable = 1 if male and the village has a boys' school	0.116	(0.161)	0.197	(0.459)	–0.301	(0.291)				
Dummy variable = 1 if female and the village has a girls' school	0.853	(0.222)***	1.518	(0.429)***	1.356	(0.633)**				
Social class variables										
Dummy variable = 1 if the household head runs a business or is an officer	0.753	(0.231)***	-0.319	(0.502)	–1.127	(0.621)*	0.346	(0.402)	1.627	(0.529)***
Dummy variable = 1 if the household head is a landowning farmer	0.441	(0.183)**	-0.504	(0.439)	–1.644	(0.663)**	–0.361	(0.373)	0.574	(0.465)
Dummy variable = 1 if the household head is a landless farmer or casual laborer	0.137	(0.146)	-0.761	(0.446)*	–1.363	(0.653)**	0.072	(0.390)	1.012	(0.542)**
Cohort variables										
Dummy variable = 1 if above the age of 40	2.417	(0.510)***	1.901	(0.618)***	2.551	(0.744)***	0.484	(0.391)	1.179	(0.600)*
Dummy variable = 1 if aged between 35 and 40	2.802	(0.593)***	1.711	(0.525)***	2.560	(0.787)***	0.562	(0.372)	0.406	(0.538)
Dummy variable = 1 if aged between 30 and 35	2.667	(0.544)***	1.801	(0.450)***	2.346	(0.748)***	0.230	(0.314)	0.077	(0.492)
Dummy variable = 1 if aged between 25 and 30	2.741	(0.568)***	1.790	(0.468)***	2.652	(0.716)***	0.131	(0.293)	0.517	(0.469)
Dummy variable = 1 if aged between 20 and 25	2.874	(0.593)***	1.738	(0.433)***	2.121	(0.672)***	0.208	(0.290)	-0.194	(0.420)
Dummy variable = 1 if aged between 15 and 20	2.688	(0.562)***	1.228	(0.451)***	2.308	(0.661)***				
Dummy variable = 1 if aged between 10 and 15	2.003	(0.517)***								
Constant	–2.699	(0.584)***	-0.053	(0.793)	0.143	(0.790)	0.822	(0.629)	-0.981	(0.655)
Number of observations	1710		693		518		417		340	

Note: * = significant at 10%; ** = significant at 5%; *** = significant at 1%. # indicates that it is unfeasible to estimate coefficients due to colinearity and hence the variable has been excluded from the estimation.

Table 6
Marginal Effects of Gender Dummy Variables from Table 5

	S_1	S_2	S_3	S_4	S_5
	$\partial P(\delta_1 = 1)/\partial x^1$	$\partial P(\delta_2 = 1)/\partial x^2$	$\partial P(\delta_3 = 1)/\partial x^3$	$\partial P(\delta_4 = 1)/\partial x^4$	$\partial P(\delta_5 = 1)/\partial x^5$
x^τ					
Female in Punjab	–0.3690	–0.1188	–0.1150	0.0098	0.0081
Female in the NWFP	–0.4311	–0.1073	–0.1502	0.0080	–0.0104

Note: The variable x^τ stands for the τ^{th} educational stage variable of our interest.

Table 7
FIML Estimation Results of the Sequential Schooling Decision Model: The Augmented Specification

	Primary school entry		Primary school completion		Secondary school entry		Secondary school completion		Postsecondary school entry	
	S_1		S_2		S_3		S_4		S_5	
	Coeff.	Std. error	Coeff.	Std. error	Coeff.	Std. error	Coeff.	Std. error	Coeff.	Std. error
Gender and region variables										
Dummy variable = 1 child living in the NWFP	0.131	(0.096)	0.359	(0.197)*	0.317	(0.287)	0.766	(0.213)***	0.658	(0.328)*
Dummy variable = 1 if female living in Punjab	–1.574	(0.333)***	-0.835	(0.512)**	–2.891	(0.508)***	0.497	(0.488)	0.943	(0.907)
Dummy variable = 1 if female living in the NWFP	–1.882	(0.350)***	-0.982	(0.603)	–1.946	(0.559)***	0.521	(0.526)	0.692	(0.815)
Sibling variables										
Number of older brothers	2.288	(2.519)	2.351	(6.291)	6.649	(8.594)	15.857	(7.630)**	14.348	(11.642)
Number of older sisters	5.127	(2.871)*	-3.291	(7.082)	16.211	(9.425)*	–2.002	(7.779)	1.136	(9.575)
Household's physical and human assets										
Amount of land owned	–1.163	(1.977)	-2.682	(2.219)	3.802	(6.570)	–0.514	(3.615)	4.836	(5.739)
Dummy variable = 1 if household owns tractor	1.343	(0.614) **	0.007	(0.473)	0.731	(0.644)	#		1.154	(0.892)
Dummy variable = 1 if the father has finished primary school	1.021	(0.216)***	0.856	(0.301)***	0.578	(0.353)	0.490	(0.288)*	0.722	(0.360)**
Dummy variable = 1 if the mother has finished primary school	0.853	(0.364)**	1.260	(0.617)**	2.122	(0.797)***	0.679	(0.538)	1.108	(0.649)
Household's shock variables										
Dummy variable = 1 if it is a good year	–0.022	(0.412)	-0.912	(0.677)	–0.281	(0.962)	–0.044	(0.450)	0.116	(0.652)
Dummy variable = 1 if it is a bad year	0.255	(0.381)	-1.513	(0.671)**	–2.242	(1.083)**	–0.543	(0.476)	0.021	(0.634)
Dummy variable = 1 if the household head has a health problem	0.112	(0.398)	-0.670	(0.567)	#		–1.628	(0.520)***	–0.755	(0.721)
Dummy variable = 1 if the wife of the household head has a health problem	0.048	(0.340)	-0.204	(0.616)	#		–0.633	(0.461)	#	
School supply variables										
Dummy variable = 1 if male and the village has a boys' school	0.123	(0.166)	0.344	(0.508)	–0.564	(0.348)				
Dummy variable = 1 if female and the village has a girls' school	0.848	(0.215)***	1.462	(0.458)***	1.466	(0.683)**				
Interaction variables										
Amount of land × Female	–0.528	(2.633)	1.456	(4.890)	–0.394	(9.872)	17.081	(11.917)	9.852	(16.736)
Good year dummy × Female	–9.417	(8.721)	9.735	(18.495)	10.311	(61.477)	–8.451	(11.700)	-11.488	(17.103)
Bad year dummy × Female	–2.377	(7.864)	-0.487	(20.684)	55.292	(90.434)	-11.109	(12.834)	12.953	(27.099)
Social class variables										
Dummy variable = 1 if the household head runs a business or is an officer	0.692	(0.223)***	-0.285	(0.524)	–1.260	(0.686)*	0.220	(0.471)	1.657	(0.804)*
Dummy variable = 1 if the household head is a landowning farmer	0.431	(0.168)**	-0.373	(0.512)	–1.741	(0.725)**	–0.351	(0.405)	0.942	(0.679)
Dummy variable = 1 if the household head is a landless farmer or casual laborer	0.129	(0.148)	-0.683	(0.426)	–1.439	(0.715)**	–0.179	(0.422)	0.887	(0.627)
Constant	–2.591	(0.534)	-0.342	(0.872)	0.471	(0.875)	0.504	(0.620)	–2.133	(0.834)
	1710		693		518		417		340	

Note: Results of cohort effects are not presented in this table. * = significant at 10%; ** = significant at 5%; *** = significant at 1%. # indicates that it is unfeasible to estimate coefficients due to colinearity and hence the variable has been excluded from the estimation.

Table 8
The Principal Reasons for Termination of Schooling

	All children		Daughters only		Heads and/or spouses who have completed primary education	
Reasons given	**Frequency**	**Percentage**	**Frequency**	**Percentage**	**Frequency**	**Percentage**
Subjective reason						
Achieved the desired level	97	13.4%	16	8.6%	36	18.7%
Economic reasons						
Education costs (tuition) too high	128	17.7%	18	9.7%	14	7.3%
Needed on farm or at home	72	9.9%	21	11.3%	15	7.8%
Got a job	55	7.6%	4	2.2%	12	6.2%
Child-specific reasons						
Child is ill	23	3.2%	7	3.8%	7	3.6%
Child got married	21	2.9%	17	9.1%	8	4.2%
Child failed in an exam	55	7.6%	9	4.8%	20	10.4%
Supply-side reasons						
Child does not want to go to school mainly because the school is too far and the teacher punishes children	235	32.5%	75	40.3%	62	32.1%
(Only "school is too far")	(44)	(6.1%)	(35)	(18.8%)	(19)	(9.8%)
Other	38	5.2%	19	10.2%	19	9.8%
Total	724	100%	186	100%	193	100%

Source: Interviews conducted as part of our survey.

Table 9
Marginal Effects of School Availability

	S_1	S_2	S_3
	$\partial P(\delta_1 = 1)/\partial z^1$	$\partial P(\delta_2 = 1)/\partial z^2$	$\partial P(\delta_3 = 1)/\partial z^3$
z^τ			
Boys' school available	0.0301	0.0042	–0.0366
Girls' school available	0.1843	0.0591	0.0113

Note: The variable z^τ stands for the τ^{th} educational stage variable of our interest.