HOUSEHOLD SCHOOLING DECISIONS IN RURAL PAKISTAN*

by

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Abstract

Field surveys were conducted in twenty-five Pakistani villages exclusively for this paper. By integrating field observations, economic theory, and econometric analysis, this paper investigates the sequential nature of educational decisions. The full-information maximum likelihood (FIML) estimation of the sequential schooling decision model uncovers important dynamics of the gender gap in education, transitory income and wealth effects, and intrahousehold resource allocation patterns. We find, among things, that there is a high educational retention rate, conditional on school entry, and that schooling progression rates become comparable between male and female students at a high level of education. Moreover, a household's human and physical assets and income changes affect child education patterns significantly. These findings are consistent with the theoretical implications of optimal schooling behavior under binding credit constraints. Finally, we found serious supply-side constraints on female primary education in the villages, suggesting the importance of supply-side policy interventions in Pakistan's primary education.

Keywords: sequential schooling decisions; income shocks; birth-order effects; supply-side constraints

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1 Introduction

The recent revival of economic growth theory has renewed interest in the nexus of human capital investment and growth (Barro and Sala-i-Martin 1995). Studies across countries show that human capital investments in Pakistan are performing poorly: the school enrollment rate is low, school dropouts are widespread, and there is a distinct gender gap in education (Behrman and Schneider 1993; Sawada 1997). Theory suggests that the low level of education in Pakistan may have a strong negative effect on the country's long-term macroeconomic growth. The microeconomic behavior of Pakistani households should underlie such a macroeconomic movement, involving the interplay of parental objectives and constraints faced by the households.

However, human capital is accumulated through a complicated decision-making process. The educational outcome is typically represented by years of completed schooling, which is a stock rather than flow variable. In this case, the current outcome depends not only on the current decision but also on past decisions. Therefore, general reduced form solutions will include the entire history of exogenous influences (Strauss and Thomas 1995, 1974-75). Yet, such historical data on individual and household characteristics are rarely available. Because appropriate data are typically missing, the dynamic aspects of education are ignored in most of the reduced form empirical literature. However, even if we have the data that theory requires, introducing dynamics by having the current period's outcome depend on past outcomes complicates the estimation procedure.

This paper attempts to overcome these two issues in the existing literature on education by making two important contributions. First, to examine explicitly the dynamic and sequential aspects of schooling decisions, we use a unique data set on the whole retrospective history of child education and household background, which was collected exclusively for this analysis through field surveys in rural Pakistan. This data collection itself contributes to the literature, shedding light on dynamic aspects of education. Second, in addition to the data contribution, this paper uses the full-information maximum likelihood (FIML) method to cope with the complicated estimation procedure of multiple integration of conditional schooling probability. This method, combined with the unique data set, enables us to estimate the full sequential model.

The estimation results of sequential schooling probabilities provide new and important insights on demand for education. In sum, five important findings emerge from our estimation. First, the most striking feature discovered is the high educational retention rate, conditional on school entry. Second, the schooling progression rates become comparable between male and female students at a high level of education. These observations indicate that parents might pick the "winners" for educational

specialization and allocate more resources to them, regardless of their gender. Third, we found that this schooling pattern can be explained partly by physical and human asset ownership and parental income and health shocks. Fourth, we found gender-specific birth-order effects that suggest resource competition among siblings. These third and fourth findings are consistent with the theoretical implications of the optimal educational investment behavior under binding credit constraints. Hence, this paper gives important new insights for understanding the dynamics of household risk-coping strategies and educational decisions in developing countries. Finally, we found that the supply side constraints of education in the village significantly restrict education, especially for females. The last finding suggests the importance of future research on the supply side management of education.

This paper proceeds as follows: Section 2 describes the key features of human capital investments in rural Pakistan, which were identified from the field research. Based on initial observations from the field, Section 3 applies the standard theory of dynamic schooling investment decisions. Based on the theoretical framework, we derive an econometric model with which we can estimate the conditional schooling probabilities in Section 4. Section 4 then shows estimation results of the empirical model. The final section offers conclusions and policy implications.

2 The Key Features Identified in the Field

Our approach follows an iterative process of (1) initial hypothesis, (2) field survey, (3) theory, and (4) empirical analysis, which is suggested by Townsend (1995). Instead of directly implementing econometric tests based on an existing well-defined data set, this paper starts with key features of household behaviors discovered in the field. Modification of data collection was undertaken in the initial stage, and the standard theory is augmented afterward according to the field observations.

Field surveys were conducted twice to gather information exclusively for this paper. In the first round of the survey in February through April 1997, the survey team carried out interviews in fourteen villages of the Fisalabad and Attock districts of Punjab province. Then the second-round surveys were conducted in eleven villages of the Dir districts of the North-West Frontier Province (NWFP) in December 1997 through January 1998. Our field surveys covered 203 households in Punjab and 164 households in NWFP. Hence, 367 households were interviewed, and information on a total of 2,365 children was collected.[1] The combined data give a complete set of retrospective histories of child

[1] The selection of our survey sites was predetermined, since we basically resurveyed the panel households that had been interviewed by the International Food Policy Research Institute (IFPRI) through the Food Security Management Project (Alderman and Garcia 1993; Alderman 1996). The initial IFPRI data collection was based on a stratified random sampling scheme. A detailed description of the procedure of our field surveys is summarized in the

schooling, together with household and village level information.

The most striking feature uncovered in the field is the high educational retention rate, conditional on school entry. According to our survey data, years of schooling averaged 1.6 years for all female children in the overall sample, whereas they were 6.6 years for male children. On the other hand, *for children who had entered primary school,* the average years of schooling become 6.0 years for girls and 8.8.years for boys. These numbers indicate that after entering school, children's years of schooling dramatically increase.

To examine the school progression rates in detail at different educational stages, we utilize the framework of estimating the conditional survival function. The Pakistani education system is composed of five years of primary education, five years of secondary education, and postsecondary education.[2] Educational outcomes can be understood as a result of five sequential schooling decisions. The first decision is whether to enter primary school (S^*_1), where S^*_τrepresents schooling time of a child at τ-th educational stage. For those who attended primary school, the second decision is whether to finish primary school (S^*_2). Then the third decision for primary school graduates is whether to continue to secondary school or stop education at grade five (S^*_3). For those who entered secondary school, the fourth decision is whether to stop before grade ten or to graduate from secondary school (S^*_4). The final decision is whether to continue beyond secondary school—that is, to enter college, technical, or teaching school (S^*_5).[3]

Let n_k denote the number of students whose have completed education of the stage of S^*_{k-1}. We simply used data where S^*_{k-1} is not right-censored at the education level k-1. The set of individuals whose school attainment is at least S^*_{k-1} is called the risk set at the k-th stage of education, $S^*_{k,}$ and thus n_k represents the size of the risk set at the level k. Among n_k students, let h_k denote the number of children who have completed education level k, and therefore $h_k = n_{k+1}$. Then, an empirical estimate of the conditional survival probability at education level k would be h_k/n_k. This number represents the fraction of students who go on to a higher stage of education, conditional on the completion of the education level k-1. Also, this can be interpreted as the sample conditional probability of school continuation to the education level k.

The estimated conditional survival or school continuation probabilities are summarized in Table 2. As we can see in Table 2, the survival rate at the first entry—that is, the probability of ever entering

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appendix.

[2] Strictly speaking, secondary education in Pakistan is composed of three years of middle education and two years of high school education.

[3] We assume that for those who did not enter a primary school, the decision was made when the child was at the age of six, which is the median age of primary school entry (Table 1). We impose similar assumptions for secondary and postsecondary education.

school—is low both for boys (64 percent) and girls (24 percent). We can also note that the female conditional schooling probability is less than half of the male conditional probability at primary school entry. After entering primary school, however, conditional primary school graduation rates become 82 percent and 69 percent for male and female students, respectively. These statistics indicate that after entering school, the majority of children remain at school. Another interesting finding is that while the conditional schooling probability is lower for girls than that for boys at primary school entry and graduation and at secondary school entry, the conditional schooling probabilities after secondary school entry are consistently higher for females in Punjab province. The gender gap in education eventually seems to disappear at the higher stages of education.[4] This finding indicates an important dynamics of the gender gap in education, which has not been pointed in the literature.

These basic statistics also suggest substantial differences in the degree of the educational gender gap among districts. According to Table 2, in the Dir district of NWFP, the conditional survival rates are consistently lower for females at all stages of the schooling decision. The district differences seem to be largely due to sociocultural factors. For example, the custom of seclusion of women, *purdah*, is strictly maintained in the Dir district. These regional divergences in gender gap in rural Pakistan raise an important policy issue. Alderman et al. (1995) pointed out that when the government allocates education expenditures, disadvantaged groups such as girls and children in lagging regions should be targeted to assure more equitable gains from schooling.

3 The Standard Theory of Educational Investments

Having discussed the key observations in the field, the next step is to formulate a formal model of the household's optimal schooling behavior, integrating the key features. A possible interpretation of the above findings is that parents might pick the "winners" for educational specialization and allocate more resources to them. As an initial theoretical framework to account for this household behavior, we employ the two sets of optimal behavioral rules. First, parents decide the intertemporal allocation of resources so as to maximize the expected total lifetime utility of the family. Second, parents also make a decision on the allocation of educational resources among children, given the overall resource constraint of the household.

[4] We also estimated the Kaplan-Meier product limit estimator, and the results are available upon request from the corresponding author. The Kaplan-Meier estimator of survival beyond stage k is the product of survival probabilities at k and the preceding periods. Graphing survival probability against sequence k produces a Kaplan-Meier survival curve. Again, at the primary school entry level, the school survival rate is much higher for males than for females. The slope of survival function, however, is flatter for females, indicating that gender gap in education becomes smaller at the higher levels of education.

We use a standard investment model of education as the benchmark and apply it to the context of rural Pakistan. The basic setup of our model is based on the seminal works by Levhari and Weiss (1974) and Jacoby and Skoufias (1997) on human capital investment under uncertainty. In particular, we extend the Jacoby and Skoufias (1997) model to a generalized form with multiple children. Essentially, risk, uncertainty, and constraints on insurance and credit influence poor Pakistani households' investment and consumption decisions. Therefore, we formalize human capital accumulation in rural Pakistan as households' sequential schooling investment decisions under uncertainty and credit constraints.

Suppose a household with n children decides household consumption, C, and schooling for child i, S_i, so as to maximize the household's aggregated expected utility with concave instantaneous utility function, $U(\bullet)$, given the information set at the beginning of time t, Ω_t. The information set, Ω_t, includes initial asset ownership and the whole history of household variables. Such a household's problem can be represented as follows:

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

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

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

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

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

In this problem, the objective function includes a concave function, $W(\bullet)$, of financial bequest and salvage value of the final stock of the child's human capital. The parameter β represents a discount factor. The first constraint is the household's intertemporal budget constraint. This household's consumable resources in each period are composed of assets, A; stochastic parental income, Y, which is a function of parents' human capital, H^P; and total child income, $\Sigma_i w_i(1\text{-}S_{it})$, with w_i being the child-specific wage rate.[5] Note that a child's total time endowment is normalized to 1. The second constraint is the human capital accumulation equation. The human capital production function, $f(\bullet)$, includes the variable q, which represents the school supply side-effect, the gender gap, and subjective factors. Among others, the variable q is a function of a time-invariant gender indicator variable that takes 1 if the child is female and

[5] We assume that a child's schooling does not change the child wage rate immediately, and accumulated human capital, H^C, is reflected in income after the child becomes an adult. In rural Pakistan, the child labor market does not seem to be segmented by level of education, since it is well known that the wage rate is not sensitive to education in rural agricultural areas (Fafchamps and Quisumbing 1999).

0 if the child is male. Also, there is an additive stochastic element e, which incorporates possibilities such as risk of job-mismatching after schooling. We assume that e is independently distributed with $E(e_{it}|\Omega_t) = 0$ for all i. The third constraint represents the potentially binding credit constraint where B is a 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_i^C., $i = 1, 2, \cdots, n$. When income is stochastic, analytical solutions to this problem, even without human capital, cannot be derived in general (Zeldes 1989). However, we can derive a set of first-order conditions that is necessary for an optimum solution, applying the Kuhn-Tucker conditions to the standard Bellman equation. In the arguments below, we will use the first-order conditions of the above problem.[6]

Now let us specify the functional forms of utility and human capital production functions. For the utility function, we assume the constant absolute risk aversion (CARA) specification.

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

Note that α represents the coefficient of absolute risk aversion. For the human capital production function, we also select the exponential function:[7]

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

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

Noting that parental human capital affects permanent income, let $Y_t^P(H^P)$ and Y_t^T represent 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 $E(Y_t|\Omega_t) = Y_t^P(H^P)$ and $E(Y_t^T|\Omega_t) = 0$. Our further 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 that following particular specification for the permanent income function: $Y_t^P(H^P) = \rho H^P t + g(H^P)$, where the first term in the right hand side represents that human capital adjusted time-trend of income with parameter ρ. The second term, $g(\bullet)$, 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 determines the evolution of optimal schooling so as to equalize the net marginal rate of transformation of human capital production and the nonstochastic market interest rate, that is,

[6] For the full derivation of the first-order conditions, see Sawada (1999).
[7] For an alternative specification of the human capital production function, see Sawada (1999).

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

Using the functional form of equation (2), the optimal schooling decision rule then approximately becomes

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

where $X\beta^{N}$ is defined as

$$X_{it}\beta^{N} \equiv \underset{\substack{\textit{Gender Gap}\\ \textit{Subjective Factor}\\ \textit{School Accessibility}}}{g_{it}} - r_{t-1},$$

where g represents the growth rate of q, which includes effects of school accessibility, gender gap, and subjective factors, and X is a matrix of proxy variables for g and r. Equation (3) 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. Hence, if the credit constraint is not binding, parental income or schooling decisions of other children do not affect the schooling decision for a child. In this case, two separabilities hold: one for consumption and schooling decisions and the other for intrahousehold schooling allocation.

Alternatively, if the household is constrained from borrowing more, the household effectively faces an endogenous shadow interest rate, which is given by the marginal rate of substitution of consumption over time. Under credit market imperfections, the separability between consumption and schooling investment decisions breaks down. The optimal condition becomes the following equalization of the marginal rate of transformation to the marginal rate of substitution:

$$\frac{\partial f / \partial S_{it}}{\partial f / \partial S_{it-1}} = \beta E_{t-1}\left[\frac{\partial U / \partial C_{t}}{\partial U / \partial C_{t-1}}\right], \forall\, i.$$

Also, note that the separability among different children's schooling decisions does not hold. Under these nonseparability properties, the reduced form schooling decision can be represented by the following linear difference equation:

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

where $X\beta^{C}$ is defined as

(4') $$X_{it}\beta^{C} \equiv \underbrace{\left(\frac{g_{it} - \ln\beta}{1+\alpha}\right)}_{\substack{\text{(I)}\\ \textit{Gender Gap}\\ \textit{Subjective Factor}\\ \textit{School Accessibility}}} + \underbrace{\frac{\alpha}{1+\alpha}(\rho H^{P} + \Delta A_{t})}_{\substack{\text{(II)}\\ \textit{Ownership and Accumulation}\\ \textit{of Assets}}} + \underbrace{\frac{\alpha}{1+\alpha}\Delta Y_{t}^{T}}_{\substack{\text{(III)}\\ \textit{Ex Post}\\ \textit{Transitory Income}}} - \underbrace{\frac{\alpha^{2}}{2(1+\alpha)}\sigma_{t}^{2}}_{\substack{\text{(III')}\\ \textit{Ex Ante}\\ \textit{Income Instability}\\ \text{(Precautionary Saving)}}} - \underbrace{\frac{\alpha}{1+\alpha}\left(\underset{j\neq i}{w_{j}\Delta S_{jt}^{*}}\right)}_{\substack{\text{(IV)}\\ \textit{Opportunity Costs of}\\ \textit{Siblings' Schooling}}}.$$

Note that ε_{it} indicates a mean zero expectation error of parental income Y_t. We allow a possibility of serial correlation of this expectation error. In our estimation, we use various proxy variables for X, which includes the following five components (equation 4'). First, X includes the gender indicator variable, the school accessibility variable, and household-specific subjective factors of educational investments. The second component of X is the ownership and accumulation of human and physical assets. The third term (III) shows that an ex post realization of transitory income of parents, ΔY_t^T, has a positive impact on child schooling. In contrast to a household with perfect credit availability, where parental income variable does not affect child schooling, a credit-constrained household faces a high marginal cost of schooling if there is a negative income shock. This reflects that consumption and schooling decisions are not separable under a binding credit constraint. The fourth term (III') shows the negative effect of income instability. This term basically indicates that, given a positive third derivative of utility function, there is a motive for precautionary saving as an 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. The final term indicates educational resource competition among siblings. For example, an increase in other children's schooling time, ΔS^*_{jt}, $\forall\, j \neq i$, or its opportunity cost, $w_j \Delta S^*_{jt}$, decreases child i's optimal level of schooling.[8] Alternatively, the wage earnings of older siblings will enhance the optimal time allocation to schooling by decreasing $w_j \Delta S^*_{jt}$.

Testable Restrictions

The important testable hypothesis can be derived by comparing equation (4) with equation (3). We can easily note that the four terms of the right-hand side of equation (4)—terms (II), (III), (III'), 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.

The economic intuition of these results should be clear. The two terms (II) and (III) in equation (4') indicate that a household's overall resource constraint and life-cycle considerations will determine the total amount of expenditure devoted to education. Credit and insurance availability become

[8] According to equation (4), the optimization behavior of a household for the ith child is conditional on that for all other children. The optimal choice of child i's schooling, S^*_i, depends on S^*_{-i}, the optimal schooling decision made for a child other than i. We therefore derived a Nash equilibrium of child educational decisions implicitly. Strategies that comprise a Nash equilibrium at each date are referred to as Markov perfect. The equilibrium represented by equation (4) can thus be interpreted as the Markov perfect equilibrium (Maskin and Tirole 1988; Pakes and McGuire

especially important at this stage. If borrowing is allowed under an exogenously given interest rate, a household can maximize the total wealth simply by investing in the human capital of each child so that the marginal rate of return from educating each child is equal to the interest rate. However, if credit availability is limited and thus household's consumption and investment decisions are not separable, the household resource availability such as parental income and assets affect the cut-off shadow interest rate for educational investments. For example, when there is an unexpected income shock, credit-constrained poor households have relatively high marginal utility of current consumption. This leads to an increase in the cut-off shadow interest rate and a decrease in child education. In this case, implicit or explicit child labor income can act as insurance that compensates for unexpected income shortfalls of parents.[9]

4 The Econometric Framework

There are two empirical approaches for investigating the schooling decision-making process, based on the basic investment model of equation (4).[10] First, the traditional approach employs a simple linear regression model for years of schooling with various household background variables as explanatory variables (Taubman 1989). However, the problem of this approach is that the linear regression model combines the sequential schooling decision process into an estimation of time-invariant parameters and therefore parameters in the model cannot be interpreted well as structural parameters.

The second approach formalized the process of schooling as a stochastic decision-making model (Mare 1980; Lillard and Willis 1994, Behrman et. al., 2000). The model explicitly investigates the determinants of sequence of grade transition probabilities. In other words, the probability of schooling at τ^{th} grade conditional on completing schooling at τ-1th grade is empirically estimated. The model has a substantial advantage over the linear regression approach since it gives estimates of structural parameters. The statistical foundation of estimating such a sequential decision-making model was first provided by Amemiya (1975). The model framework was then applied to estimation of schooling grade probabilities

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1994; Besley and Case 1993).

[9] In fact, many estimates of schooling function using household data sets from developing countries report positive coefficients of current household income variables, which imply the existence of credit market imperfections (Behrman and Knowles 1999; King and Lillard 1987; Sawada 1997).

[10] In fact, a third approach consists of applying the structural estimation framework for a dynamic stochastic discrete choice model. For a literature survey, see Amemiya (1996) and Eckstein and Wolpin (1989). Yet, given a household having n children, the household's schooling choice set is composed of 2^n mutually exclusive, discrete dependent variables. Since n takes about seven on average in our households from Pakistan, the structural estimation of such a model will be computationally intractable. Applications of this framework to development issues include estimates of the gender and age specific values of Korean children (Ahn 1995), an analysis of sequential farm labor decisions using Burkina Faso's data (Fafchamps 1993), well investment decisions in India (Fafchamps and Pender 1997), bullock accumulation decisions of Indian farmers (Rosenzweig and Wolping 1993), and an analysis of fertility

with family background characteristics as determinants of these probabilities. For example, using a Malaysian data set, Lillard and Willis (1994) estimated the sequential schooling decision model, controlling for individual unobserved heterogeneity. Cameron and Heckman (1998) constructed an alternative choice-theoretic model to examine how household background affects the school transition probabilities. Other papers focus on only one transition out of the many sequences of schooling process, such as the transition probability of high school graduates (Willis and Rosen 1979).

We will follow the second econometric approach and estimate the sequential schooling decision model jointly. To estimate probabilities of the sequential decisions with an assumption of serial correlation, we employ the full-information maximum likelihood method. Recall that there are the three levels of education in Pakistan: primary, secondary, and postsecondary. Educational outcomes are assumed to result from the five sequential decisions, as discussed in Section 2.

To formalize the sequential schooling process, we can define an indicator variable of schooling:

(5) $$\delta_{i\tau} = 1 \text{ if } S^*_{i\tau} > 0$$
$$= 0 \text{ otherwise,}$$

where τ indicates the τth stage of education and S^* is a latent variable and corresponds to the schooling time variable, S^*, in equation (4). Note that $\delta_{i\tau} = 1$ if child i goes to school at the τth stage of education. We discretize the years of schooling into five categories, and thus τ takes on five values. With this new discrete variable, the sequential process of schooling decision is described as follows: children are born with zero years of schooling. If children become the age of six or so, some children enter primary school, while other children stay uneducated. The uneducated children with *no* primary school entry, $S^*_{i1} = 0$, is represented by the indicator variable $\delta_{i1} = 0$. Having entered primary school ($S^*_{i1} > 0$ and $\delta_{i1} = 1$), some children finish primary school ($\delta_{i2} = 1$ or $S^*_{i2} > 0$) while other children drop out from primary school ($\delta_{i2} = 0$ or $S^*_{i2} \leq 0$). Then, of those children who have finished primary school, some enter secondary school ($\delta_{i3} = 1$ or $S^*_{i3} > 0$), while others do not ($\delta_{i3} = 0$ or $S^*_{i3} \leq 0$). Given entered secondary school, some children finish secondary school ($\delta_{i4} = 1$ or $S^*_{i4} > 0$), while other children do not ($\delta_{i4} = 0$ or $S^*_{i4} \leq 0$). Finally, after finishing secondary school, some children enter postsecondary school ($\delta_{i5} = 1$ or $S^*_{i5} > 0$), although others do not ($\delta_{i5} = 0$ or $S^*_{i5} \leq 0$).

By rewriting equation (4), the estimation equation for child i can be represented by

(6) $$S^*_{i\tau} = X_{i\tau}\beta_\tau + u_{i\tau},$$

where $\tau = 1, 2, \cdots, 5$, and $u_{i\tau} \equiv S^*_{i\tau\text{-}1} + \varepsilon_{i\tau}$. X is assumed to include the gender indicator variable, the school supply variables, determinants of the household preference, household shock variables, and the

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decisions using Malaysian data (Wolpin 1984).

sibling composition variables. Note that $S^*_{i0} = 0$ by construction.

Under an assumption that the decision making is independent across stages, or equivalently, $u_{i\tau}$ is independent across τ, the sequential model of equation (5) and (6) can be estimated by maximizing the likelihood functions of dichotomous models repeatedly (independent error term specification) (Amemiya, 1975). However, our theoretical result indicates that schooling decisions are not independent across stages by construction. It is straightforward to show that $\mathrm{Cov}(S^*_{i\tau}, S^*_{i\tau-1}) \neq 0$, since $u_{i\tau} \equiv S^*_{i\tau-1} + \varepsilon_{i\tau}$. These correlations can be explained, for example, by some unobserved propensity for schooling that is stronger among the children who graduated from a certain grade than among the children who did not finish this grade.

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

(7) $$Pr\,(S^*_{i5} > 0, S^*_{i4} > 0, S^*_{i3} > 0, S^*_{i2} > 0, S^*_{i1} > 0)$$

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

The direct calculation of such a high-dimensional integral is computationally involved and maybe infeasible, as the integral must be evaluated at each step of the likelihood maximization. There are two possible ways to deal with the problem. Both ways rely on the fact that the unconditional joint distribution (7) can be presented as a weighted sum of products of univariate distributions. If no assumptions are made about the form of the joint distribution of the error terms of (6), $u_{i\tau}$, 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 an assumption of joint normality, the distribution of the error terms of (6) can be approximated using Gauss-Hermite quadrature (see Judd 1998). The first method imposes fewer restrictions on the error structure in the system of equation (6), but it is less stable computationally. The likelihood function that results from nonparametric estimation of the error distribution (7) is highly nonlinear, and our maximization algorithm fails to find a global optimum. An approach based on Gauss-Hermite quadrature demonstrated much better convergence properties in our case, and this is the method we use for our estimations (we will refer to this method as FIML further in the text). The log-likelihood function $\Im$ for the system of equations (6) is then:

$$\Im = \sum_{n=1}^{N} Log\left\langle \sum_{m_1=1}^{M_1} w_1 \sum_{m2=1}^{M_2} w_2 \sum_{m3=1}^{M_3} w_3 \sum_{m4=1}^{M_4} w_4 \left[\prod_{\tau=1}^{5} PR^{\tau}\left(X_{i\tau}\beta_{\tau} \mid v_{m_1}, v_{m_2}, v_{m_3}, v_{m_4}\right) \right] \right\rangle$$

where N is total number of observations in the sample, $PR^{\tau}(\bullet)$ are the cumulative distribution functions

for every equation in system (6) conditional on the common factors, v's and w's are one-dimentional quadrature points (nodes) and weights from a Gauss-Hermite rule (Stroud and Secrest 1966), M's are the numbers of quadrature points. As before, X's represent the equation specific sets of explanatory variables and β's are the vectors of unknown parameters to be estimated.

The estimations presented in the paper are based on the approximation of the probability integral by Gauss-Hermite quadrature with four nodes.[11] Further increase in the number of nodes fails to improve the value of log-likelihood function. Identification is achieved through inclusion of the set of stage-specific variables such as school supply variables, household human and physical assets, and household income and health shock variables, as will be discussed 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 error distribution.[12]

5.1 Variables

As we estimate the above sequential schooling model, we start by inspecting the basic data characteristics. According to the median age of school entry, children enter primary schools at the age of six, secondary schools at the age of eleven, and postsecondary schools at the age of seventeen (Table 1). Moreover, our survey data show that primary and secondary education last an average of five and six years, respectively. Since the formal length of the secondary-level schooling is five years in Pakistan, an extra year in secondary education in our sample indicates that grade repetition or a delay of secondary school entry, which is quite common in Pakistani villages.

Table 3 summarizes descriptive statistics of variables used in the sequential model of equation (6) as the discrete dependent variable, S^*_{it}, and covariates of conditional probabilities, X. According to our theoretical model (4), X is assumed to include gender gap indicator variables, school supply variables, subjective discount factor, physical and human assets, transitory income change, and sibling composition variables.

The gender gap indicator variables are divided into two subgroups according to province. The first gender variable is for Punjab province and is a dummy variable taking 1 for females in Punjab

[11] Parameters of the model are estimated by maximum likelihood using 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, 263).

[12] Results of the independent error term specification are available from authors upon request. While the independent error term model is thought to provide biased coefficients owing to correlations of sequential decisions, qualitative results of the independent error model and the FIML estimates are comparable.

province and 0 otherwise. Similarly, the second gender dummy variable for NWFP takes 1 for females in NWFP and 0 otherwise. These female dummy variables indicate that the share of female students declined at the primary school entry level (Table 3).

The second block of independent variables contains the gender-specific school supply variables. The first supply variable takes 1 only if the child is male and there is a male school within the village of the child's residence. Otherwise, this variable takes 0. The second supply dummy variable takes 1 only if the child is female and there is a female school within the village. We can see that for primary school entry level, 37 percent of male children do not face supply constraints, whereas only 18 percent of girls have access to female schools in their village (Table 3).[13]

Third, we assume that a household's subjective preference depends on the household's social class or caste status. Traditionally, the caste status, called *biraderi* in Punjab and *quom* in NWFP, is identified with an occupational position (Eglar 1960; Ahmad 1977; Barth 1981; Ahmed 1980). For example, agricultural landless laborers are strictly distinguished from landowners. Nonagricultural laborers such as casual laborers and artisans are also differentiated from landowners. This system of caste has prevailed in the form of social norms, and members of each class are expected to act according to their social and economic status. Hence, the caste system indirectly constrains the educational opportunities of low-caste children. In order to capture these sociocultural effects, we include parents' occupation dummy variables—farmers with land, landless farmers or nonfarm casual laborers, and business and government officials. The default variable is those who are unemployed and/or at home because of sickness or unemployment. According to Table 3, more than 30 percent of our sample is composed of farmers with land for all schooling processes. It is notable that, at higher schooling stages, the fraction of children from landless farmers or casual laborers declines significantly. On the other hand, the share of children of farmers with land ownership increases after secondary school entry. These casual findings are consistent with the sociocultural background of Pakistani society.

The fourth set of variables is composed of household human and physical asset variables.[14] The first two variables are time-invariant dummy variables for father and mother's education, which take 1 if the father or mother has completed at least primary school and take 0 otherwise. Household physical asset variables include the amount of land ownership and a dummy variable for tractor ownership. We can easily see that all four of these household asset variables increase as the child education level increases (Table 3). Children who are studying at higher levels of education are basically from relatively

[13] 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 education.

[14] Although our theory requires us to include asset accumulation as independent variables, we utilize a total asset variable instead of its first difference. This is simply because markets for land and agricultural machinery are thin in

rich households of educated parents.

With respect to the transitory income shock variables, the model includes good- or bad-year dummy variables based on household's subjective and retrospective assessment of agricultural production, wage earnings, and livestock income. The health shock effects are also considered by including dummy variables for the health of the household head and the wife, which take 1 if they are physically inactive and take 0 otherwise. As Jacoby and Skoufias (1997) pointed out, a distinction between unanticipated and anticipated components of transitory income movements might be important. The health shocks might be interpreted as the unanticipated components since these shocks are largely unexpected. On the other hand, income movements include both anticipated and unanticipated components.

As sibling variables, we take the number of older brothers and sisters. Alternatively, we can incorporate more detailed sibling composition variables, separated by current schooling status. Yet, our o*lder* sibling variables are predetermined, and thus we may be allowed to regard these variables as being exogenous. The descriptive statistics show that there is a negative relationship between education level and the number of older brothers and sisters (Table 3). This finding suggests that those students who could obtain higher education are from households with a small number of children. This can be a reflection of intrahousehold resource competition or birth-order effect.

Finally, according to the age distribution of sampled children of the household head, the average age of children is 20.5 in 1998. However, there is a large variation in age. Some members are older than 50. The age distribution indicates that there will be a potentially large cohort effect, and thus the empirical model needs to control for it. Hence, we include age cohort dummy variables.

5.2 Estimation Results of the Sequential Schooling Decision Model

Columns in Table 5 summarize a set of estimated coefficients of the full sequential schooling decision model for each school level. These results are a derived FIML estimation of conditional probabilities represented by equations (7) and (8). Detailed descriptions and interpretations of our FIML estimation results are presented below.

Gender Gap

First, coefficients on gender dummy variables indicate that daughters have lower conditional schooling

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rural Pakistan and thus we do not observe change in assets frequently.

probabilities at the primary entry and exit levels than sons have. The female coefficients in Punjab province are smaller than those in NWFP at the primary school entry, indicating a smaller gender gap in Punjab. This regional difference seems to be largely due to the different degree of sociocultural constraints. Yet the coefficients on the female dummy variable are not statistically significant after secondary school entry. The gender gap in education seems to disappear among the students who are studying at secondary and postsecondary level schools. Therefore, schooling progression rates become comparable between male and female students at higher levels of education. Table 6 summarizes the discrete marginal change of schooling probabilities with respect to gender dummy variables, evaluated at mean dependent variables.[15] We can easily verify that the marginal effects are different between girls and boys at the primary school entry level, while the difference disappears at the secondary school exit level. These marginal effects confirm the above interpretation of the estimation results in Table 5.

Development researchers and practitioners have argued that women are significantly less educated than men in Pakistan (Khan 1993; Shah 1986; Chaudhary and Chaudhary 1989; Behrman and Schnieder 1993). There are several possible explanations for the distinct gender gap in education. For example, the high opportunity costs of daughters' education in rural Pakistan may lead to apparent intrahousehold discrimination against women in terms of education. Because of the custom of seclusion of women, *purdah*, parents might have a strongly negative perception of female education. However, our estimation results represent that evidence is not so simple or monotonic. Although there is a distinct gender gap in primary-level education, the gap is likely to disappear among those who have entered secondary education.

School Supply

The school availability coefficients are positive and significant for female schools, while the coefficient is not statistically significant for male schools. This result suggests that the lack of primary and secondary schools in the village clearly impedes female education, while supply-side constraints are not severe for male students. The marginal effect of primary school availability within the village is represented in Table 7.[16] According to Table 7, accessibility to a primary school within the village seems to contribute

[15] To calculate the marginal effects in a given simulation, the certain value of the variable of interest is assigned to all the households in the sample in a particular state. The simulated probabilities are generated for each household by integrating over the estimated distribution and averaging the probabilities across the sample. Next, the value of the variable of interest is changed, and this changed value is assigned to the whole sample of the households. Then the 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 a difference in these simulated probabilities.
[16] See footnote 15 for explanations of our methodology to calculate the marginal effects.

to a 18 percent increase in a girl's primary school entry probability. Moreover, female primary school drop out will decline by 16%. In fact, our qualitative survey data show that, in 32.5 percent of school termination decisions, households listed the supply side as the main reason for their decision problems, including inaccessibility to school and the low teacher quality (Table 4). A significant portion of the gender gap in Pakistani education may be explained by supply-side quantity and quality constraints (Alderman et al. 1995, 1996). Although traditional Pakistani culture requires single-sex schools, the lack of school availability affects female education more seriously than male education (Shah 1986). Parents are unwilling to send daughters to school if a female school is not available nearby. Since allowing girls to cross a major road or a river on the way to school often involves the risk that daughters will break *purdah*, parents will choose not to let daughters go to school. Moreover, sociocultural forces also create the needs for women teachers to teach female students in the village. It has been pointed that irrespective of the monetary or nonmonetary incentives in the form of scholarships, girls will come only if schools are opened with female teachers in each village (Chaudhary and Chaudhary 1989).[17] Even if a girl's school is available in the village, a chronic shortage of women teachers imposes serious constraints on female education.

Social Class Effects

The overall estimated coefficients of the social class variable indicate that, at primary and postsecondary entry levels, children of business or government official households have the highest schooling probability among the social classes considered. The second finding is that the farmers with land ownership have higher level of educational investments at the primary school entry level than landless farmers or casual labor households. These results suggest that the occupation, which is traditionally related to social status, affects educational investment decisions at the initial entry decision to schools and at higher levels of education.

[17] Although the supply of teachers is constrained in part by the shortage of women candidates, the village environment also prevents expansion of female teachers in rural areas. Attracting and retaining high-quality female teachers from outside villages poses a different set of problems, since they must relocate, gain local acceptance, and clear the difficult hurdle of finding suitable accommodations. Even locally recruited teachers could be chronically absent from school because of responsibilities for their household chores (Khan 1993). Nevertheless, there is not enough monetary compensation to attract women to be teachers. Provincial governments, for instance, provide teachers in villages with lower allowances for house rent than teachers in urban areas. Moreover, there might be a

Parental Human Assets

Father and mother's education variables have consistently positive and significant coefficients in all levels of schooling except at the secondary school exit level. These estimation results indicate important complementarity between the education of the parents and the child schooling investments. This complementarity is generated possibly by educated parents' positive incentive of educating children, improved technical or allocative efficiency, and/or superior home teaching environments, as pointed out by the preceding studies (Schultz 1964; Welch 1970; Behrman and others 2000). Subjective factors might be important as well. According Table 4, in 13.4 percent of cases, households listed "the accomplishment of the desired education level" as the primary reason of a child's school dropout. This is a purely subjective reason, implying that schooling choice may differ depending on ethnicity, network, and social status (Psacharopoulos and Woodhall 1985). The more educated mother and father seem to be better able to perceive the benefit of education than uneducated parents, since they can estimate returns to education more precisely.

Household Physical Assets

At the primary school entry decision, while the tractor ownership variable has a positive and significant coefficient, land ownership has a negative significant coefficient. This asymmetry in two physical assets might be attributable to the difference in complementarity with education. In poor Pakistani villages, tractor ownership is an obvious measure of a household's wealth. Hence, our results suggest that the primary school entry probability of children is systematically higher for households with wealth. Moreover, it has been argued that technology and education have complementarity (Psacharopoulos and Woodhall 1985; Foster and Rosenzweig 1996). It is likely that tractor operation requires at least a basic level of education. On the other hand, the negative coefficient of land ownership at the primary school entry level might suggest that there is a complementarity between land ownership and on-farm child work, which results in less education of children.

At the postsecondary education entry level, both tractor and land ownership have positive and statistically significant coefficients on the conditional schooling probability. At this level, household ownership of physical assets seems to play an important role in education decisions. In general, households' resource availability extends their self-insurance ability and thus encourages high-risk and high-return investment opportunities. Risk-taking and precautionary saving behaviors may be closely

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school quality problem originating from the teacher's low level of education (Warwick and Jatoi 1994).

related to physical asset ownership (Morduch 1990). The negative effect of accumulating precautionary saving on educational investment will be less severe for those households that have assets.

Household Shock Variables

Negative income shocks discourage schooling continuation significantly at the primary school exit and the secondary school entry and exit levels. Moreover, negative health shocks increase dropouts from secondary school. These estimation results are favorable to our theoretical model under binding credit constraints (Equation 4). In general, Pakistani households face considerable income instabilities. Risks of disaster such as large income shortfalls, sickness, and sudden death of an adult member impose serious constraints on a household's resources, since there is a severe limitation on formal and/or informal insurance and credit availability in rural areas. Accordingly, exogenous negative shocks have non-negligible effects on the household's educational investment decisions. Pakistani households might adopt perverse informal self-insurance devices by using child labor income as parental income insurance, sacrificing the accumulation of human capital.[18]

Sibling Competition

According to the estimated coefficients in the sibling variables block, the number of older sisters seems to be associated with more primary education for younger siblings. This finding is consistent with Greenhalgh (1985) and Parish and Willis (1993) using Taiwanese data. Older sisters may extend the household's resource availability, either by marrying early or by providing domestic labor. This suggests that households are not discriminating against all daughters, although the older daughters might bear a large portion of burden under binding resource constraints (Strauss and Thomas 1995).

On the other hand, at the secondary school exit and postsecondary entry levels, the number of older brothers, instead of the number of older sisters, increases schooling probabilities. These results suggest that once a child is picked as a "winner" of educational investment within the family, his or her education at the secondary and postsecondary level is supported partly by the older brother's resource contributions. At these higher levels of education, an older brother's farm or nonfarm monetary income contributions to household resources might be more important and significant than a daughter's nonmarket domestic labor contribution to the household.

[18] Sawada (1997) and Alderman et. al. (2000) also found the important impact of shocks on school enrollments in rural Pakistan.

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

6 Concluding Remarks

This paper investigated the sequential educational investment process of Pakistani households by integrating observations from the field, economic theory, and econometric analysis. The paper makes two contributions to the literature. First, we use the unique data set on the whole retrospective history of child education and household background, which was collected exclusively for this analysis through field surveys in rural Pakistan. Second, in addition to the data contribution, this paper employed full-information maximum likelihood method to cope with the complicated estimation procedure of multiple integration of conditional schooling probability. This method, combined with the unique data set, enabled us to estimate the full sequential model of schooling decisions.

The most striking feature revealed by the data is the high educational retention rate, conditional on school entry. Moreover, we found important dynamics of the gender gap in education, the significance of shock variables, wealth effects, and intrahousehold resource allocation with our full sequential schooling model. These findings are consistent with a household's optimal education investment under a binding credit constraint.

Although the demand for education cannot be controlled directly by the government, supply-side interventions will be effective. Our estimation results suggest that, in addition to household demand considerations, raising the quantity of female primary schools has a substantial effect in improving

[19] There are two possible cases (Behrman and Taubman 1986). The first possibility is a negative birth-order effect. As more children are born, the household resources constraint becomes severe and fewer resources are available per child. If this per child resource shrinkage effect is dominant, the younger (higher-order) siblings will receive less education than older siblings. Alternatively, the 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. This is the case of positive birth-order effects. Also, an economy of scale due to household-level public goods might exist, since siblings can share various educational inputs and materials. Positive knowledge externalities might be important as well, since younger children can learn easily from the experience of their older siblings through home teaching. In sum, having older siblings might promote the education of a younger child, rather than impede the education of that child, if the resource extension effects, scale economies, and externalities are larger than the competition effects.

education in Pakistan. Indeed, the push to expand access to schooling by increasing the supply of schools has dominated the agenda for education in developing countries since the 1960s (Lockeed et al. 1991). Yet remote and inappropriate female school locations and resultant high schooling costs are still serious problems in rural Pakistan. Hence, the cost-effectiveness of providing primary education can be significantly improved, if the allocation of funds is shifted toward recurring expenditures for construction of female schools and employment of more female teachers. These supply-side policy interventions have significant potential for reducing gender biases in human capital investment. We should also note that closing the gender difference in education creates long-lasting positive effects on economic development, since education of mothers relates to fertility and population over time. Many empirical studies show a highly educated mother has lower infant mortality rate, fewer children, and more educated and healthier children (King and Hill 1993).

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Appendix: A Summary of the Field Survey

Field surveys were conducted twice to gather information exclusively for this paper. In the first round of the survey in February through April 1997, the survey team carried out interviews in fourteen villages of the Fisalabad and Attock districts of Punjab province (Sawada, 1999). The selection of our survey sites was predetermined, since we basically resurveyed the panel households that had previously been interviewed by the International Food Policy Research Institute (IFPRI) through the Food Security Management Project, based on a stratified random sampling scheme (Alderman and Garcia 1993). The first district in our sample, Faisalabad, is a well-developed irrigated wheat and livestock production area. The second district, Attock, is a rainfed wheat production region near the industrial city of Taxila. In this district earnings from nonfarm activities are the major component of household income. Then the second round surveys were carried out in eleven villages of the Dir district of the North-West Frontier Province (NWFP) in December 1997 through January 1998. Dir is also a rainfed wheat production area with some cash crop production such as citrus. There is a limited set of nonfarm income-earning opportunities within and around the district. However, temporary emigration to the Persian Gulf countries is common in Dir. As a result, nonfarm income and remittances account for more than 60 percent of average household income, according to the IFPRI data files (Sawada 1999).

In our retrospective surveys, we used three different sets of questionnaires. The first questionnaire is composed of questions on basic child information and retrospective schooling progress. The second questionnaire collects basic household background information, such as household size, permanent components of household resources, and fluctuations in household assets and income over time. With the third questionnaire, village-level retrospective information was gathered by interviewing local government officials and/or educated village dwellers such as schoolteachers. In particular, we collected information about the year when male and female primary schools were built in the village.

These questionnaires seemed to work well in the field. Farmers remembered 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. We visited the villages without prior notification, and the availability of respondents was uncertain in advance. Therefore, we may plausibly assume that our attrition of panel households is determined by a random process.

Our field surveys covered 203 households in Punjab and 164 households in NWFP. Hence, 367 households were interviewed, and information on a total of 2,365 children was collected. The combined data set gives a complete set of retrospective histories of child schooling, together with household- and village-level information, which make the estimation of a full sequential schooling decision model feasible. 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 part of the IFPRI data files that contains long-term retrospective information on household and village characteristics.

Table 1
Distribution of Age at School Entry

Percentile [OK as edited?]	Primary school	Middle school	Secondary school	Postsecondary school
Youngest 10%	5	10	13	16
25%	6	11	14	16
Median	6	11	14	17
75%	7	12	15	18
90%	8	13	16	20
Mean age (standard deviation)	6.43 (1.74)	11.64 (1.73)	14.69 (2.11)	17.23 (2.54)
Coefficient of variation	0.2706	0.1486	0.1436	0.1474
Number of observations	1,150	685	451	177

Table 2
Sample Probability of School Continuation

		Total		Faisalabad		Attock		Dir	
		Male	Female	Male	Female	Male	Female	Male	Female
Primary school entry	h_1/n_1	0.64	0.24	0.65	0.33	0.69	0.34	0.62	0.17
Primary school graduate	h_2/n_2	0.82	0.69	0.74	0.72	0.87	0.69	0.84	0.67
Secondary school entry	h_3/n_3	0.93	0.53	0.97	0.34	0.89	0.59	0.94	0.64
Secondary school graduate	h_4/n_4	0.59	0.71	0.47	0.87	0.53	0.75	0.68	0.62
Postsecondary school entry	h_5/n_5	0.57	0.57	0.55	0.77	0.39	0.56	0.64	0.48
Total number in sample	n_1	978	872	232	185	221	176	525	511

Table 3
Descriptive Statistics

	Code	Primary entry S_1*	Primary exit S_2*	Secondary entry S_3*	Secondary exit S_4*	Postsec. entry S_5*
Dependent variable						
Dummy variable takes 1 if S_τ* = 1; takes 0 if S_τ* = 0, where τ = 1, 2, …,	S_τ*+	0.45	0.79	0.85	0.61	0.57
Gender variable						
Dummy variable = 1 if female in Punjab	pu_gen+	0.20	0.14	0.13	0.07	0.09
Dummy variable = 1 if female in NWFP	nw_gen+	0.28	0.10	0.09	0.07	0.07
School supply variable						
Dummy variable = 1 if male and there is a male school within the village	p_sup_m+	0.37	0.64	0.23		
Dummy variable = 1 if female and there is a female school within the village	p_sup_f+	0.18	0.19	0.03		
Social class variable						
Dummy variable = 1 if household head is farmer with land	farm_wl+	0.30	0.37	0.37	0.42	0.37
Dummy variable = 1 if household head is landless farmer or casual laborer	casual+	0.44	0.33	0.32	0.27	0.27
Dummy variable = 1 if household head runs business or is officer	bus_gov+	0.17	0.23	0.24	0.23	0.26
Household human and physical assets						
Dummy variable = 1 if father has finished primary	fed+	0.19	0.29	0.31	0.31	0.36
Dummy variable = 1 if mother has finished primary	med+	0.02	0.05	0.05	0.06	0.08
Amount of land ownership	p_land	13.39 (37.51)	16.85 (45.27)	17.35 (43.83)	21.31 (48.85)	22.31 (53.85)
Dummy variable = 1 if owns tractor	p_trac+	0.01	0.03	0.03	0.04	0.06
Household's shock variables						
Dummy variable = 1 if good year	p_good+	0.07	0.05	0.02	0.33	0.06
Dummy variable = 1 if bad year	p_bad+	0.06	0.06	0.02	0.33	0.06
Dummy variable = 1 if household head is inactive	p_hinact+	0.05	0.06	0.002	0.31	0.02
Dummy variable = 1 if wife of household head is inactive	p_winact+	0.06	0.05	0.01	0.32	0.04
Sibling variables						
Number of older brothers	m_old	1.83 (1.87)	1.77 (1.82)	1.69 (1.63)	1.69 (1.63)	1.67 (1.56)
Number of older sisters	f_old	1.56 (1.68)	1.57 (1.64)	1.52 (1.57)	1.53 (1.56)	1.50 (1.55)
Cohort variables						
Dummy variable = 1 if above age of 40	age40+	0.11	0.08	0.09	0.09	0.10
Dummy variable = 1 if age between 35 and 40	age3540+	0.09	0.10	0.10	0.11	0.12
Dummy variable = 1 if age between 30 and 35	age3035+	0.12	0.14	0.15	0.15	0.16
Dummy variable = 1 if age between 25 and 30	age2530+	0.16	0.21	0.22	0.23	0.21
Dummy variable = 1 if age between 20 and 25	age2025+	0.17	0.23	0.24	0.23	0.26
Dummy variable = 1 if age between 15 and 20	age1520+	0.13	0.17	0.16		
Dummy variable = 1 if age between 10 and 15	age1015+	0.07				
Number of observations	N	1,850	833	658	557	340

+ indicates dummy variable. Numbers in parentheses are standard deviation

Table 4
The Most Important Reason for a Child's School Termination

Reason given	Frequency	Percent
Subjective reason		
Accomplished the desired level	97	13.4
Economic reasons		
Education costs too high (tuition)	128	17.7
Needed on farm or at home	72	9.9
Got a job	55	7.6
Child-specific reasons		
Child is ill	23	3.2
Marriage	21	2.9
Child failed in exam	55	7.6
Supply-side reasons		
School is too far	44	6.1
Child does not want to go to school (Mainly, teacher's punishments)	191	26.4
Other	38	5.2
Total	724	100

Source: Author's interview.

Table 5
FIML Estimation Results of the Sequential Schooling Decision Model

	Primary entry		Primary exit		Secondary entry		Secondary exit		Postsecondary 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 variable										
Dummy variable = 1 if female living in Punjab	-1.455	(0.152)***	-1.516	(0.569)***	-3.306	(0.359)***	0.165	(0.454)	0.443	(0.447)
Dummy variable = 1 if female living in the NWFP	-1.716	(0.134)***	-1.111	(0.571)**	-2.759	(0.453)***	-0.062	(0.466)	-0.475	(0.523)
School supply variable										
Dummy variable = 1 if male and there is a male school within the village	0.163	(0.140)	0.320	(0.423)	-0.304	(0.285)				
Dummy variable = 1 if female and there is a female school within the village	0.748	(0.129)***	1.190	(0.414)***	1.463	(0.640)**				
Social class variable										
Dummy variable = 1 if household head is farmer with land	0.436	(0.143)***	-0.359	(0.424)	-1.582	(0.645)**	-0.549	(0.374)	0.391	(0.450)
Dummy variable = 1 if household head is landless farmer or casual laborer	0.178	(0.136)	-0.593	(0.419)	-1.331	(0.641)**	-0.022	(0.394)	0.835	(0.439)*
Dummy variable = 1 if household head runs business or is officer	0.719	(0.164)***	-0.262	(0.471)	-1.088	(0.670)*	0.256	(0.433)	1.600	(0.500)***
Household human and physical assets										
Dummy variable = 1 if father has finished primary	0.868	(0.112)***	0.543	(0.268)**	0.734	(0.310)**	0.221	(0.258)	0.555	(0.329)*
Dummy variable = 1 if mother has finished primary	0.818	(0.320)**	1.046	(0.571)*	2.438	(0.748)***	0.644	(0.478)	1.140	(0.549)**
Amount of land ownership	-1.971	(1.116)*	-0.673	(2.136)	5.504	(4.793)	1.465	(2.508)	9.201	(4.692)*
Dummy variable = 1 if owns tractor	1.199	(0.451)***	-0.416	(0.541)	0.377	(0.653)	#		1.246	(0.593)**
Household's shock variables										
Dummy variable = 1 if good year	-0.074	(0.270)	-0.361	(0.539)	-0.653	(0.890)	-0.236	(0.360)	0.047	(0.531)
Dummy variable = 1 if bad year	0.095	(0.291)	-1.031	(0.510)**	-1.202	(0.635)*	-1.075	(0.341)***	0.105	(0.533)
Dummy variable = 1 if household head is inactive	0.034	(0.337)	-0.781	(0.521)	#		-1.795	(0.447)***	#	
Dummy variable = 1 if wife of household head is inactive	-0.021	(0.300)	-0.191	(0.564)	#		-1.017	(0.418)**	-0.793	(0.600)
Sibling variables										
Number of older brothers	1.321	(2.199)	-0.801	(5.514)	5.186	(7.622)	20.098	(6.634)***	25.433	(8.588)***
Number of older sisters	4.934	(2.406)**	-1.259	(5.998)	12.774	(8.752)	4.393	(6.834)	6.596	(9.210)
Cohort variables										
Dummy variable = 1 if above age of 40	2.164	(0.216)***	1.679	(0.600)***	2.539	(0.605)***	0.340	(0.422)	1.181	(0.594)**
Dummy variable = 1 if age between 35 and 40	2.532	(0.218)***	1.330	(0.488)***	2.522	(0.601)***	0.445	(0.411)	0.537	(0.528)
Dummy variable = 1 if age between 30 and 35	2.376	(0.196)***	1.447	(0.443)***	2.321	(0.548)***	0.171	(0.349)	0.140	(0.491)
Dummy variable = 1 if age between 25 and 30	2.505	(0.191)***	1.612	(0.426)***	2.830	(0.533)***	0.066	(0.309)	0.597	(0.460)
Dummy variable = 1 if age between 20 and 25	2.554	(0.189)***	1.475	(0.414)***	2.212	(0.505)***	0.080	(0.312)	-0.166	(0.425)
Dummy variable = 1 if age between 15 and 20	2.463	(0.194)***	1.077	(0.422)**	2.567	(0.544)***				
Dummy variable = 1 if age between 10 and 15	1.843	(0.210)***								
Constant	-2.354	(0.243)***	0.474	(0.762)	0.625	(0.821)	1.005	(0.509)**	-1.760	(0.704)**
Number of observations	1,850		833		658		557		340	

Note: * = significant at 10%; ** = significant at 5%; *** = significant at 10%.
# indicates that it is infeasible to estimate coefficients due to colinearity and thus dropped from estimation.

Table 6
Marginal Effects of Gender Dummy Variables

	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					
Male	0.6558	0.8314	0.8887	0.5987	0.5713
Female in Punjab	0.2485	0.5149	0.3281	0.6206	0.6563
Female in NWFP	0.1908	0.6539	0.43095	0.5900	0.4770

Note: See footnote 15 for the calculation formula of the marginal effects. The variable x^τ stands for the τ-th education stage variable of our interest.

Table 7
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			
Male/school available	0.039	0.050	-0.037
Female/school available	0.177	0.157	0.126

Note: See footnote 15 for the calculation formula of the marginal effects. The variable z^τ stands for the τ-th education stage variable of our interest.