HOW DO MOTHERS’ EDUCATIONAL ATTAINMENTS AFFECT
THE EDUCATIONAL ATTAINMENT OF THE NEXT GENERATION?*

(Preliminary)

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1. INTRODUCTION

The structure of intergenerational socioeconomic mobility is a fundamental aspect of social inequality, social organization, and social change. Mobility patterns convey substantial information about inequality of opportunity, the rigidity of stratification systems, the potential for class conflict, and how social hierarchies persist from one generation to the next. Analyses of intergenerational mobility are centrally concerned with estimating the effects of family socioeconomic background on a variety of socioeconomic outcomes for offspring. Whether based on multivariate models of educational and occupational status attainment, econometric models of intergenerational income correlations, or tables of occupational or class mobility, mobility research focuses on how parents’ socioeconomic positions affect the positions of their offspring. At the individual or family level, this research is an effort to answer questions about who gets ahead, inequality of opportunity, and the potential benefits to children of improvements in their parents’ socioeconomic positions. In the aggregate, this research attempts to show how changes in the distributions of parents’ socioeconomic characteristics contribute to changes in the corresponding distributions for their offspring.

Social scientists aptly describe social mobility and its variations across time and place, and across dimensions of socioeconomic inequality. Yet whereas many analysts of intergenerational processes estimate the associations between the socioeconomic characteristics of parents and offspring, they are less successful in establishing that parents’ characteristics are in fact causes of the characteristics of their offspring. Researchers use multivariate models to isolate the net effects of parents’ socioeconomic statuses by controlling for many confounding and intervening variables. But this is insufficient to establish that a change in the socioeconomic characteristics of parents would necessarily lead to a change in their children’s achievement. Sobel (1998), for example, shows that estimates of effects from these models do not approximate the estimates that would be obtained from the variations in socioeconomic outcomes that would result from randomly assigning children to families. In a related vein, Behrman and Rosenzweig (2002) among others argue that unmeasured factors confound observed associations between parents’ and offsprings’ characteristics that might otherwise have a social or economic
interpretation. They suggest, for example, that efforts to improve the life chances of the offspring generation by raising the educational attainments of mothers may be fruitless because the apparent “effects” of mother’s educational attainment on the schooling of their children are the spurious result of unobserved genetic linkages between parents and offspring and marriage market sorting effects. As Sobel suggests, social mobility research is useful as description, but largely unsuccessful in showing how individual or aggregate changes in parental characteristics affect subsequent generations. Causal inference may be possible only in rare circumstances where a data collection scheme makes it possible to control for almost all confounding factors.

Causal inference, however, depends not only on random assignment of persons to social environments, but also on an understanding of the mechanisms through which intergenerational effects may occur. Although the problems created by nonrandom assignment and “omitted variables” in the analysis of intergenerational effects are widely appreciated, almost all discussions of intergenerational mobility give an inadequate account of how generations of men and women affect the socioeconomic attainment of subsequent generations. Even if children were randomly assigned to families, or unobserved causes of socioeconomic attainment were controlled by other means, causal inference would not be possible without a clear understanding of the mechanisms through which one generation affects the next. To see how parents’ characteristics affect those of their offspring, it must be possible, in principle, to manipulate those characteristics to yield an outcome different from what would otherwise occur. But conventional mobility studies are ill-suited to assessing the effects of this type of intervention. Because mobility analysis typically focuses on relationships between parents and offspring conditional on existing mother-father and parent-child relationships, rather than on the unconditional relationships between parent and offspring generations, it is inadequate for assessing the effects of feasible changes in parental characteristics. Even if random assignment of individuals to different family background strata were somehow achieved, the resulting causal inferences from otherwise conventional approaches to the study of intergenerational relationships would be of questionable relevance to practical and theoretical questions about the impact of family background on the next generation. Conversely, if causal inferences are not warranted and one’s goals remain descriptive, conventional approaches yield incomplete descriptive results. A more encompassing demographic model that reveals the unconditional relationships between the characteristics of successive generations is needed both for causal inference and adequate description.
In this paper we argue that the models typically used in mobility studies are inadequate for assessing the intergenerational impact of socioeconomic characteristics. We propose alternative models that provide improved estimates of intergenerational effects. To elucidate these ideas and models we focus on the effects of women’s educational attainments on the education of the subsequent generation. Our models enable one to estimate the unconditional effects of interventions to raise the schooling of women in the maternal generation and to show how these effects work through marriage, fertility, and intergenerational transmission. This enables us to go beyond standard approaches, which estimate effects of mothers’ schooling conditional upon the existence of mother-child pairs. Our models build upon models for aggregate projections of socioeconomically differentiated populations. The models presented here differ from those that have appeared in prior literature in that we estimate them using information on the marriage, fertility, and child characteristics for individual women. Thus, they allow for common, unmeasured heterogeneity of women and families within measured categories of educational attainment. Correlations of unobserved determinants of women’s fertility, marriage behavior, and child outcomes may alter our assessments of the intergenerational effects of women’s schooling.

The balance of this paper is as follows. In Section 2 we argue that the assessment of effects of women’s schooling on the educational attainment of subsequent generations requires that one focus on differential fertility and marriage, in addition to the relationship between mother’s and children’s educational attainment. The unconditional relationship between the educational attainments of successive generations is the mechanism through which the intergenerational effects of efforts to raise the educational attainments of women are likely to occur. Section 3 briefly reviews educational and demographic patterns in Indonesia, an interesting population in which to study the effects of changing women’s educational attainments. In Section 4 we describe our models of intergenerational effects. Section 5 describes the Indonesian Family Life Survey, which we use to estimate our models of intergenerational effects, and discusses our estimation and simulation methods. Section 6 presents our empirical results, including simulations of the intergenerational effects of hypothetical interventions to raise educational attainment in the maternal generation and comparisons with more conventional estimates of family background effects. Section 7 summarizes our main findings and conclusions. Section 8 is a postscript that discusses our ongoing work on this topic.
2. CONDITIONAL AND UNCONDITIONAL INTERGENERATIONAL EFFECTS: WOMEN’S EDUCATIONAL ATTAINMENTS

The intergenerational effects of changes in the socioeconomic characteristic of adults occur partly through individual or family level variables that intervene between those characteristics and the characteristics of the offspring generation. These “indirect” effects, a staple of intergenerational mobility research, are inferable from data on the characteristics of parents and children in existing families. By themselves, these are conditional effects in that they depend on existing mother–father and parent–child relationships. Intergenerational effects also occur through mechanisms that alter the numbers and types of families in which children are raised. If changing people’s characteristics alters their propensity to marry, the types of persons they marry, or the number of children that they have, this too will alter the distribution of socioeconomic outcomes in subsequent generations. These effects, however, cannot be inferred from existing mother–father and parent–child relationships alone. The unconditional effects of changes in adult socioeconomic characteristics incorporate the marriage and fertility processes, in addition to the effects of parents on children conditional on marriage and the birth of a child.

The Effects of a Change in Women’s Educational Attainment

In this paper we focus on the effects of women’s educational attainments on the educational attainments of subsequent generations. Mother’s schooling is often viewed as a key determinant of the welfare of her children. In populations with low average maternal educational attainment or a large gap in education between men and women, it may be possible to improve the lives of both women and their children by removing barriers to their advancement in school. Consider the effect of mother’s educational attainment on the attainment of her daughter or son. If mother’s attainment is a cause of her child’s attainment, then one may ask: what is the effect on children of a hypothetical policy of changing the schooling of an individual woman, of an entire cohort of women, or some targeted subgroup of women? This question raises important issues of research design and model specification. Regression estimates based on samples of offspring can at best show the impact of changing a woman’s attainment level conditional upon

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1 Behrman and Rosenzweig (2002) enumerate a number of recent economic studies that are motivated by this premise and offer a skeptical view of the presumed intergenerational benefit of raising women’s schooling.
her giving birth to the sampled child and, if father’s or other family characteristics are controlled in the analysis, upon her marriage. Even if this conditional estimate were satisfactory in principle, one faces the usual complications of confounding by omitted variables that are correlated with mother’s educational attainment, as well as specifying how other measured variables, such as family structure and number of siblings transmit the effects of mother’s schooling or are jointly determined with offspring’s schooling (Mare 2001).

But this kind of conditional estimate may be quite unsatisfactory for many purposes, including attempts to assess the effects of feasible interventions in women’s lives. Women complete most – if not all -- of their schooling prior to childbearing and, in most societies, prior to meeting the fathers of their children. A change in a woman’s educational attainment may alter the number and timing of the children that she bears, as well as whether, when, and whom she marries. Thus, the estimate of the impact of mother’s education depends on whether it is assumed that she has already given birth, has not yet given birth but has formed a union with a child’s (potential) father, or has not yet taken a partner. At the individual level, fertility and marriage are thus intervening mechanisms between a woman’s educational attainment and the attainment of her children. More fundamentally, it is impossible to discern the full impact of changing a woman’s educational attainment by conditioning on the observation of her sampled child. Rather, the intergenerational impact of a woman’s education on her offspring’s education is weighted by the number and timing of her children, her marital status and the characteristics of her spouse or partner. In the population, moreover, the impact of a change in the average level or the distribution of women’s schooling must take full account of both the intergenerational correlation of educational attainments and also the population renewal process.

**Differential Fertility**

To assess the impact of a change in women’s schooling in the parents’ generation on the distribution of education in a later generation, it is necessary to examine their separate effects on marriage, childbearing, and the educational attainment of children. Women’s marital status, age at marriage, husbands’ characteristics, and fertility are potentially affected by women’s education. For individual women, these characteristics intervene between her education and the educational attainment of her offspring. At the population level, these processes alter the relative numbers of children who achieve various levels of education attainment. For a given distribution
of women’s educational attainment and conditional effects of mothers on children, the resulting distribution of offspring’s schooling may differ between populations that have different patterns of differential fertility by mother’s educational attainment. Within one population, moreover, the effect of a change in the distribution of women’s education on the educational attainment of the next generation may vary depending on whether it increases the numbers of women in high or low educational strata. In a population in which fertility and educational attainment are negatively correlated, the beneficial effect on the next generation of an increase in average education of women will be dampened by the tendency of more educated women to have fewer children than their less educated counterparts. In contrast, in a population in which the relationship between education and fertility is nonmonotonic, the size of the effect of an increase in women’s educational attainment will depend on whether more women move into the higher or lower part of the education-fertility schedule. In short, differential fertility among women with varying educational attainments weights women by their number of offspring and thus alters the relative numbers of offspring to whom the conditional effects of mother’s schooling apply.

A woman’s educational attainment may affect the timing as well as the level of her fertility. For individual children, this may affect their attainment because children born later in their mothers’ lives tend, ceteris paribus, to go further in school than children born to young mothers (Mare and Tzeng 1989). For the population this may alter the education distribution of subsequent generations by modifying the relative growth rates of the offspring of different education classes of mothers. Early fertility results in more rapid population growth than later fertility (e.g., Keyfitz 1985). This effect, however, is almost always much smaller than the fertility level effect on population growth and may be further muted in populations with high levels of intergenerational educational mobility (Mare 1997).2

Marriage, Marriage Timing, and Assortative Mating

Marriage also affects the educational reproduction process through a variety of avenues. For individual families, mother’s marital status and father’s educational attainment affect the educational attainment of offspring. At the population level marriage behavior alters the education distribution of the next generation through its effect on levels and differentials in

2 Fertility timing effects are not included in the analyses reported in this paper. As discussed in Section 7, we will incorporate them into future versions of our models.
fertility. For example, if highly educated women are relatively more likely to remain single or to marry very late, their fertility will be reduced and thus their capacity to raise the average education level of the next generation will be dampened. Similarly, patterns of educational resemblance between women and their husbands may modify differential fertility patterns in a complex way depending on the respective education-related fertility schedules of men and women. In a marriage market where women’s educational attainment has a large effect on the type -- that is, the education level -- of the man she marries, an increase in women’s average educational attainment may enhance or suppress the effects of women’s educational differentials in fertility.

**Educational Change and Unobserved Characteristics of Women**

Thus far we have discussed only the effects of changes in women’s educational attainments that are unrelated to any of her other characteristics. Yet unobserved characteristics of women may alter the effect of a change in women’s educational attainment. Women who have relatively high fertility are not a random sample from all women. Within levels of educational attainment, the women who choose to have more children may be those who are most able to offer advantages to their offspring. Alternatively, high fertility women may be those with the poorest prospects for achievement in the labor market and talent and opportunity in the labor market are positively correlated with the ability to raise successful offspring. Depending on which of these possibilities is more prevalent, the conditional association between mother’s and offspring’s achievement may over or underestimate the true effect of mother’s educational attainment -- that is, the effect that would be likely to be observed from a change in the education distribution of women.

Unobserved factors may also modify the aggregate effects of a change in women’s education distribution on the next generation, even if these unobserved characteristics are initially uncorrelated with women’s attainment. Consider an intervention that moves, say, 50 percent of women who are in the lowest education stratum to the next highest education stratum and leaves the women’s education distribution otherwise unchanged. The potential effect of this intervention depends on how these women are chosen. If the women who are given more schooling are selected at random from the lowest stratum, then unmeasured characteristics of women have no direct impact on the effect of the intervention. Alternatively, if the women who
are given more schooling are more likely to be chosen from among women who are more likely to marry a more educated man, to have lower fertility, or to invest in their children, the heterogeneity distribution may have an important effect on the education distribution of the next generation. The size of this effect, however, will depend on the correlation of such unmeasured factors across the marriage, fertility, and intergenerational transmission processes.

Related Literature


The approach discussed in this paper extends this prior research in two important ways. First, it uses a model of socioeconomic and demographic reproduction to develop new methods of estimating the effects of family socioeconomic background on educational attainment. That taking account of marriage and fertility may alter one’s assessment of intergenerational effects is only implicit in these prior studies. Second, it develops models of intergenerational mobility, fertility, and marriage that take account of unobserved heterogeneity within categories of observed socioeconomic characteristics. All the studies cited above use traditional demographic
methods of obtaining estimates of fertility and mortality, assortative mating, and intergenerational mobility from independent data sources and projecting the population. These methods assume that the population is homogenous within categories of measured variables and thus that these processes are independent at the individual level. Our models, in contrast, allow for common unmeasured characteristics of mothers to influence marriage, fertility, and offspring’s educational attainment.

We also build upon another important line of research, which examines the intergenerational effects of parents’ characteristics. Within the large economic and sociological literature on this subject, those studies that take account of unobserved as well and observed sources of intergenerational correlation are particularly relevant. Lillard and Willis (1994) examine intergenerational mobility across multiple generations, taking account of unobserved permanent family-level factors. Lillard and Kilburn (1995, 1996) develop related models for family effects on earnings, taking account of intergenerational transmission and assortative mating. Behrman, Rosenzweig, and Taubman (1994) and Behrman and Rosenzweig (2002) use data on twins to develop models of intergenerational educational mobility and assortative mating. These econometric models of kinship and mobility, however, are all based on the conditional associations between parents and offspring and between husbands and wives. That is, they focus on parent offspring relationships conditional upon the relationships that occur, rather than treating marriage and fertility patterns as themselves contingent upon the education levels of parents. These models, therefore, are ill-suited to assessing the full intergenerational impact of a change in parental education on the distribution of outcomes in the next generation.

3. WOMEN’S EDUCATION EFFECTS IN INDONESIA

We investigate these issues and illustrate alternative estimates of the intergenerational effects of women’s educational attainment using data for Indonesia. We rely on the Indonesian Family Life Survey (IFLS), which we discuss in Section 5. Indonesia has the world’s fourth largest population and is the largest predominantly Muslim nation. Most important for our work, average levels of educational attainment among Indonesian women are low relative to most North American and European nations, although they have increased markedly among recent cohorts of young women.
Indonesia has also undergone huge demographic changes during the past 30 years, including massive declines in fertility and mortality rates and substantial rural to urban migration. Total fertility has declined markedly during the past 30 years, dropping from 5.6 children per woman in 1971 to 2.6 children in 1999 (Badan Pusat Statistik, Republik Indonesia). Despite the fertility decline, marriage remains nearly universal among Indonesian women. For example, in 1980, 78 percent of 20-24 year olds, 94 percent of 25-29 year olds, and 97 percent of 30-34 year old women were married (Hirschman and Guest 1990).

During this period, the average educational attainment levels and sex differentials have changed dramatically as well. For example, among men born in 1930-34, 27 percent had no formal schooling and 92 percent had no more than primary school. For women in this cohort 56 percent had no formal schooling at all and 97 percent had no more than primary school. For men born in 1960-64 in contrast, only 5 percent had no formal schooling and 36 percent had more than primary schooling. For women, these corresponding percentages were 10 and 23 percent respectively (Cobbe and Boediono 1993). More recent cohorts show still higher levels of educational attainment and smaller differences between men and women.

Fertility in Indonesia varies substantially by women’s educational attainment, although it does not follow a simple inverse relationship. Among Indonesian women in the 1970s, fertility was highest for women with primary education, lowest for the small proportion of women with post-secondary schooling, and at an intermediate level for women with no schooling or secondary schooling (Hirschman and Guest 1990). This curvilinear pattern has persisted in more recent years, as shown by the authors’ calculations discussed in Section 5.

Although the arguments and models discussed in this paper are applicable to any population, Indonesia is a very suitable context within which to consider the potential impact of hypothetical interventions to raise the educational attainments of women and to examine the interdependence of demographic and socioeconomic change. Because Indonesia has undergone a substantial demographic and educational transformation during the past two generations, moreover, it is also a fruitful context for examining how well our models can predict these major demographic and social changes.
4. MODELS FOR THE INTERGENERATIONAL EFFECTS OF WOMEN’S EDUCATIONAL ATTAINMENTS

We are interested in how a population of women with varying amounts of education, produces a generation of offspring who also vary in their educational attainment, taking account of three processes: (1) marriage, including whether and whom to marry; (2) differential fertility, as affected by marital status and mother’s and father’s education; and (3) the intergenerational transmission of educational status. Most research on intergenerational mobility is exclusively focused on (3), whereas (1) and (2) are essential parts of the reproduction process too.

In the following discussion, we ignore the timing of fertility and marriage and assume that everything happens all at once for a given cohort or, equivalently, a generation at a time. We present a modified one-sex model in that we focus on the contribution of women and mothers to the reproduction of the population, but allow marital status and husband’s educational attainment to affect fertility and intergenerational transmission. It is not a two-sex model because the marriage market is completely female-dominated. We assume that whatever kind of man a woman wants (at least, with respect to his education), she can get.

Let \( D_j \) be the number of persons in the offspring generation with education level \( j \), \( M_i \) be the number of women in the mother generation with education level \( i \), and \( r_{ijk} \) be the number of children who attain education level \( j \) per woman who has attained education level \( i \), and has a husband with education level \( k \). Let \( i = 1, \ldots, 5; j = 1, \ldots, 5, k = 0, 1, \ldots, 5 \). Thus, education has five discrete, but ordered levels. When \( k = 0 \), a woman remains unmarried. Then:

\[
D_j = \sum_{i=1}^{5} \sum_{k=0}^{5} r_{ijk} M_i .
\]

Given the \( r_{ijk} \) we can compute the expected number of children of education level \( j \) born to a mother with education level \( i \). If the processes governing the \( r_{ijk} \) are time-invariant, and we know the education distribution of women at a given date, then this equation can project the education distribution of women for successive generations. In a similar vein, we can simulate what would happen to \( D_j \) if the distribution of \( M_i \) were modified.

A variety of models are available to estimate the \( r_{ijk} \). These models vary in sophistication depending on whether or not they distinguish the three demographic processes that govern these rates; whether or not the separate processes are estimated jointly from a common set of data or
“piece-wise;” and by whether or not they allow for heterogeneity in the \( r_{ijk} \) within categories of women’s education, husband’s education, and parity. These possibilities are considered below.

**Joint Estimation, No Heterogeneity, No Separation of Processes**

A simple model for the \( r_{ijk} \) is based on observed children born to women. An event count model for numbers of offspring is:

\[
\log(r_{ijk}) = \lambda + \lambda_i^W + \lambda_j^D + \lambda_k^H + \lambda_{ij}^{WD} + \lambda_{jk}^{WH} + \lambda_{jk}^{DH} + \lambda_{ijk}^{WDH},
\]

where the \( W, D, \) and \( H, \) superscripts refer to coefficients for categories of woman’s (mother’s) education, offspring’s education, and husband’s (father’s) education respectively and parameters involving the first category of any of these variables are normalized to zero. Because \( r_{ijk} \) is a rate, we proceed as follows. We cross classify women (in the mother generation) by women’s educational attainment, husband’s educational attainment (including “unmarried” as noted above), and offspring’s educational attainment. Within this classification, let the number of offspring be \( d_{ijk} \) and the number of mothers be \( m_{ijk} \). Because \( r_{ijkl} = d_{ijkl}/m_{ijkl} \), (2) can be estimated as a poisson or negative binomial regression model for \( \log(d_{ijkl}) \) with \( \log(m_{ijkl}) \) as an offset (Agresti 2002, pp. 385-387).

This approach is feasible if we have enough data on women’s completed fertility and the educational attainments of their offspring. Although the effects of mother’s and father’s education and family size are included in the estimating equation, this model does not explicitly represent the three processes that we are interested in. Nor does it allow for heterogeneity within levels of mother’s and father’s education and fertility. By developing a model that distinguishes fertility, marriage, and intergenerational transmission, we can allow for unmeasured heterogeneity, and identify the separate components of the intergenerational transmission process.

**No Heterogeneity, Separation of Processes**

The \( r_{ijk} \) arise from the joint processes of marriage, fertility, and intergenerational transmission. We can express these rates as follows:

\[
r_{ijk} = p_{ijk}^D r_k^D p_{ki}^H,
\]
where $p_{ijk}^D$ denotes the probability that a child with a mother at the $i^{th}$ education level, and a father at the $k^{th}$ education level will attain the $j^{th}$ level of education; $r_{ik}$ is the expected number of children born to women in the $i^{th}$ education category who are married to men in the $k^{th}$ education category; and $p_{ki}^H$ is the probability that a woman in the $i^{th}$ education category marries a man in the $k^{th}$ education category. Each of these components can be modeled separately or in a joint model that explicitly parameterizes the three processes.

The probabilities $p_{ijk}^D$ can be expressed as a multinomial logit model in which the covariates include mother’s and father’s educational attainments:

$$
P_{ijk}^D = \frac{\exp(\alpha_j + \alpha_{ji}^W + \alpha_{jk}^H + \alpha_{jik}^{WH})}{\sum_{j=1}^5 \exp(\alpha_j + \alpha_{ji}^W + \alpha_{jk}^H + \alpha_{jik}^{WH})},$$

where $\alpha_t = \alpha_{ij}^W = \alpha_{ik}^H = \alpha_{jik}^{WH} = 0$. The rates $r_{ik}$ can be expressed as an event count model (poisson or negative binomial) for fertility, in which the covariates include mother’s and father’s educational attainment:

$$\log(d_{ik}) = \log(m_{ik}) + \beta_i + \beta_{ik}^W + \beta_{ik}^H + \beta_{ik}^{WH}.$$

The probabilities $p_{ki}^H$ can be expressed as a multinomial logit model in which the covariates include categories of women’s educational attainment.

$$p_{ki}^H = \frac{\exp(\gamma_k + \gamma_{ki}^W)}{\sum_{k=0}^5 \exp(\gamma_k + \gamma_{ki}^W)}.$$

These models are recursive in that mother’s schooling precedes marriage and father’s schooling, which precedes fertility, which precedes offspring’s schooling. It is possible to estimate each of the three equations separately. The marriage equation requires only a cross classification of adult women’s education, their marital status, and the educational attainment of their husbands. The fertility equation requires a table of completed fertility rates specific to mother’s and father’s educational attainment and mother’s marital status. The transmission equation requires a cross classification of offspring’s educational attainment by her mother’s and father’s educational attainment.
Joint Estimation, Heterogeneity, Separation of Processes

Equations (4), (5), and (6) assume no systematic unmeasured heterogeneity within the joint categories of the independent variables. Further, they assume that the three processes are independent. If, however, unmeasured woman level factors affect each of these processes, the independence assumption is false and estimates may be inconsistent. In addition, it is possible that failure to take account of woman-level heterogeneity will distort our simulated effects of women’s schooling and intergenerational projections. To take account of unmeasured heterogeneity, we allow for a woman-specific component in each equation. Then, for the \( t \text{th} \) woman:

\[
P_{jikt}^D = \frac{\exp(\alpha_{jt} + \alpha_{jikt}^W + \alpha_{jikt}^H + \alpha_{jikt}^{WH})}{\sum_{j=1}^S \exp(\alpha_{jt} + \alpha_{jikt}^W + \alpha_{jikt}^H + \alpha_{jikt}^{WH})},
\]

\[
\log(d_{it}) = \beta_i + \beta_{it}^W + \beta_{it}^H + \beta_{it}^{WH},
\]

and

\[
P_{kit}^H = \frac{\exp(\gamma_{it} + \gamma_{kit}^W)}{\sum_{j=0} \exp(\gamma_{it} + \gamma_{kit}^W)},
\]

where each equation now includes woman-specific random intercepts that follow an assumed probability distribution. If the intercepts for individual women are correlated across the three parts of the model, the rates and probabilities that we estimate are correlated, a property that must be incorporated into an assessment of the effects of women’s educational attainment on the next generation. Because (5’) is an equation for individual women each observation has an offset of zero. Offspring from the same mother share common intercepts \( \alpha_{jt} \).

An interesting feature of the model that includes unobserved heterogeneity components is that it also provides, at least in principle, unconditional estimates of the effects of parents’ on offspring’s schooling at the family level. Although we are unaccustomed to thinking of models of intergenerational mobility as being subject to a selectivity bias, women who are most likely to invest in their children may have differential fertility and marriage behavior apart from what is

\[3\] These models can also be augmented to include sibship size, which is endogenous to the model, as shown in equation (5). In future versions of the analyses presented in this paper, we will include sibship size as a regressor.
predicted on the basis of her observed educational attainment alone. Models that do not take account of this interdependence of marriage, fertility, and intergenerational transmission may yield inconsistent estimates of the effects of mother’s and father’s educational attainment on offspring’s schooling. The estimated correlations between the determinants of marriage, fertility, and offspring educational attainment provide an indication of the degree to which unobserved determinants of marriage and fertility may also affect offspring’s educational attainment. These inferences, however, can only be suggestive in the absence of exclusion restrictions and instrumental variables for identifying the selection effects. As the models have been presented here, such selection effects are identified by functional form restrictions.

In the empirical implementation of these models in the present paper, we estimate somewhat simpler specification than those discussed here. These are described in Section 5 below.

5. DATA AND METHODS

Indonesian Family Life Survey

Our analyses are based on the Indonesian Family Life Survey (IFLS), a longitudinal household sample first interviewed in 1993 (IFLS1) and followed up in 1997 (IFLS2), 1998 (IFLS2+), and 2000 (IFLS 3). The IFLS is a comprehensive socioeconomic and health survey, containing detailed information on demographic and socioeconomic characteristics, household economy, health, fertility and marriage histories, and child cognitive and health assessments. Information on educational attainment is obtained for all respondents and spouses, children, and parents of respondents. Because the survey includes interviews with multiple household respondents, it obtains both self and proxy reports of educational attainment for many individuals. The survey represents an area that includes 13 of Indonesia’s 26 provinces and 83 percent of its population. We use the public domain data from the 1993 and 1997 waves. The 1993 data consist of interviews with the members of 7224 households, including all household heads and their spouses, two randomly selected children between the ages of 0 and 14, a randomly selected remaining individual aged 50 or older and her/his spouse, and, for 25 percent

Observations on multiple offspring of the same mother permit the identification of a random effect for the progeny of each woman separate from a woman-level effect that is identified from the correlated marriage, fertility, and
of households, a randomly selected remaining individual between the ages of 15 and 49 and her/his spouse. The IFLS2 survey attempted to interview all surviving respondents to IFLS1 plus all members of IFLS1 households who were born in 1968 or earlier. Because IFLS2 obtained a complete enumeration of persons in the 1993 households, it provided a more adequate sample of persons who were not household heads, spouses of heads, or children of heads than the 1993 survey. The 1997 survey also followed IFLS1 household members who formed new households and included their spouses and children as well. For detailed IFLS documentation, see Frankenberg and Karoly (1995) and Frankenberg and Thomas (2000).

Our analyses use two interdependent samples of IFLS respondents and their offspring. Only observations with complete data on woman’s, husband’s, and children’s schooling and woman’s age and marital status are included. These samples include:

_Husband’s Education/Fertility Sample._ 3963 IFLS2 ever married female respondents aged 41 and over. These observations are used for assessing the effects of women’s educational attainments on the educational attainment of the husband that she is able to marry and her number of children ever born. For the approximately 20 percent of ever-married IFLS female respondents who had married more than once, we use the educational attainment of the husband to whom she was married for the longest period between her ages 15 and 40. This sample is approximately representative of ever married Indonesian women aged 37 and over in the target sample areas of the IFLS in 1993.

_Intergenerational Transmission Sample._ 3611 offspring aged 18 and over of IFLS2 female respondents. Many but not all off these offspring were themselves IFLS2 respondents. The offspring are relatively young: Approximately 35 percent are aged 18-20, 40 percent are 21-25, 16 percent are 26-30, and the remainder is older than 30. This sample is approximately representative of the offspring over 18 of married women in the target sample areas of Indonesia in 1993.

The IFLS records 13 possible levels of educational attainment: (1) none, (2) some elementary, (3) completes elementary, (4) some junior secondary, (5) completes junior secondary, (6) some senior secondary, (7) completes senior secondary, (8)–(11) various post-secondary diplomas below university first degree, (12) university attendance, and (13) university degree or higher. Taking account of sample size constraints, we collapsed (2) and (3), (4) and (5), (6) and (7), and (8)–(13) into categories for junior secondary, senior secondary, and post-intergenerational transmission processes. This separate component is not included in the models presented here.
secondary respectively. Table 1 summarizes the education distributions of women, husbands, and children for each of the relevant samples. These distributions show the substantial intergenerational increase in educational attainment between mothers and their adult children. For example, at the extremes of the education distribution, 25 percent of mothers had no formal schooling and less than 2 percent achieved any post-secondary education. In contrast only 3 percent of their adult children failed to attend school whereas more than 15 percent went beyond secondary school. Among older IFLS female respondents, women achieved substantially lower education levels than their husbands. Approximately 75 percent more wives than husbands had no formal schooling, whereas twice as many husbands as wives had post-secondary schooling.

**Estimation**

In the models for which estimates are presented in this paper, we adopt simpler specifications of equations (4') and (6'). We specify the effects of parents’ schooling on the attainment of their offspring as an ordered logit model with a woman-specific random intercept instead of a multinomial model and obtain only additive effects of parents’ schooling. That is,

\[
P_{jt|ik}^D = \frac{\exp(\kappa_j - \alpha_i + \alpha^W_H + \alpha^H_H)}{1 + \exp(\kappa_j - \alpha_i + \alpha^W_H + \alpha^H_H)} - \frac{\exp(\kappa_{j-1} - \alpha_i + \alpha^W_H + \alpha^H_H)}{1 + \exp(\kappa_{j-1} - \alpha_i + \alpha^W_H + \alpha^H_H)} ,
\]

where the \(\kappa_j\) denote the cutpoints of the cumulative distribution of offspring’s education (with \(\kappa_0 = -\infty\) and \(\kappa_5 = \infty\)). We also omit unmarried women from the equation for marital status/husband’s education and specify the effects of women’s educational attainment as an ordered logit model with a woman-specific random intercept. That is,

\[
P_{kt|i}^H = \frac{\exp(\rho_k - \gamma_i - \gamma^W_H)}{1 + \exp(\rho_k - \gamma_i - \gamma^W_H)} - \frac{\exp(\rho_{k-1} - \gamma_i - \gamma^W_H)}{1 + \exp(\rho_{k-1} - \gamma_i - \gamma^W_H)} ,
\]

where the \(\rho_j\) are the cutpoints of the cumulative distribution of husband’s education (with \(\rho_0 = -\infty\) and \(\rho_5 = \infty\)). In practice multinomial and ordered logit models predict very similar offspring and husband’s education distributions. We will include unmarried women in future analyses.\(^5\) Equations (5’), (7), and (8) are estimated both as separate equations and also jointly as a three equation system. In the single equation models the unobserved heterogeneity components are assumed to be constant over women; that is , \(\alpha_t = \alpha\); \(\beta_t = \beta\); and \(\gamma_t = \gamma\) for all \(t\). In the three-

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\(^5\) An alternative approach is to retain the ordered logit model for husband’s schooling and to add a fourth, binary response equation to the model for whether or not the woman is married. The combined ordered logit and binary
equation model the unobserved heterogeneity components vary across women and are assumed to follow a trivariate normal distribution with mean vector zero and covariance matrix:

\[
\begin{pmatrix}
\sigma^2_{\alpha} & \sigma_{\alpha\beta} & \sigma_{\alpha\gamma} \\
\sigma_{\alpha\beta} & \sigma^2_{\beta} & \sigma_{\beta\gamma} \\
\sigma_{\alpha\gamma} & \sigma_{\beta\gamma} & \sigma^2_{\gamma}
\end{pmatrix}
\]

Because (7) is an ordered logit model estimated on individual women, \( \sigma^2_{\alpha} \) is not identified and thus we constrain it to one. Equation (8) is also an ordered logit model, but \( \sigma^2_{\gamma} \) is nonetheless identified from the multiple adult children that we observe for many female IFLS respondents. The covariance elements of (9) are all identified. Models are estimated using GLLAMM, a Stata module for maximum likelihood estimation of Generalized Linear Latent and Mixed Models (StataCorp 2003; Rabe-Hesketh, Pickles, and Skrondal 2001).

Simulation

We use the parameter estimates from our models to compute the expected distributions of offspring’s schooling that are implied by alternative assumptions about the educational attainment distributions of the mother’s generation and about the ways that women’s attainment affects her marriage, fertility, and the attainment of her children. For models with no woman-specific random intercepts, we use predicted probabilities of a woman marrying a man at each level of educational attainment, predicted number of children born, and predicted probabilities of children achieving each level of educational attainment that are implied by parameter estimates and actual or hypothetical values of observed characteristics of women and their husbands. For models that include woman-specific random effects, we compute predicted probabilities or numbers of children that incorporate woman-specific posterior means of the three latent variables in our models. In both cases these predicted results can be combined to yield an expected number of children at each level of educational attainment for each woman. That is,

\[
r_{ijkl} = p_{ijkl}^D p_{ij}^H p_{kj}^M,
\]

where all notation is as defined above. Given the \( r_{ijkl} \), the expected number of persons in the offspring generation who attain the \( j \)th education level is \( n_j = \sum_i \sum_k \sum_r r_{ijkl} \). As discussed in logit models yield predictions of the husband’s education distribution very similar to those from the multinomial
further detail below, the $r_{ijkl}$ are computed under a variety of scenarios that vary with (1) the hypothetical change in the education distribution of the mothers’ generation, (2) the presence or absence of woman-specific unobserved heterogeneity, and (3) the presence or absence of variation in the three components of $r_{ijkl}$ that are included in equation (10) (that is, which of women’s education effects on marriage, fertility, and child’s schooling are taken into account in a simulation).  

6. EMPIRICAL RESULTS

Parameter Estimates

Tables 3 and 4 report our parameter estimates for models without and with unobserved women-specific heterogeneity respectively. Figures 1-5 show the predicted education probabilities or predicted number of children for each model. All equations are restricted to married women or their adult children. Women’s, husbands’, and children’s schooling are measured in the five categories discussed. In the fertility and intergenerational transmission equations, the models assume discrete, additive effects of women’s and husband’s schooling. (We find no evidence of nonadditive parents’ effects.) The log likelihood for the multi-equation model, when compared to the sum of the log likelihoods for the single equation models, indicates that the model that includes common unobserved sources of variation in marriage, fertility, and children’s educational attainment fits much better than the model that ignores these factors. The estimated covariance matrix for woman-specific random effects shown at the bottom of Table 4, implies a negative correlation between the unobserved determinants of husband’s educational attainment and of number of children ever born ($\rho = -.68$) and a positive correlation between unobserved determinants of husband’s and children’s educational attainments ($\rho = .36$).

Indonesian couples show strong evidence of positive assortative mating. For example, Figure 1 shows that the percentages of women who marry men with at least a senior secondary education increases monotonically from less than two percent for women with no formal

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6 These simulations all assume that women’s educational attainments change through a random draw of women at given level of educational attainment. In our ongoing work we also consider the potential effects of changes in the women’s education distribution that depend on where a woman falls in the heterogeneity distribution.
schooling to more than 60 percent for women with post-secondary schooling. This strong positive relationship does not vary markedly depending on whether unobserved women-specific heterogeneity is estimated or not.

The single-equation estimates of the effects of parents’ schooling on number of children ever born follow the concave pattern of differential fertility observed in other research on Indonesia. Holding the husbands’ distribution constant, women’s expected number of children vary from approximately 4.0 for women with no formal schooling to a high of 4.3 for women with junior secondary education to a low of 2.8 for women with post-secondary education (see Figure 2). The curvilinear pattern of fertility by husband’s education is less sharp than for women. Holding constant women’s educational attainment, husbands with primary, junior, or senior secondary schooling all have approximately four children, whereas men at the top and bottom of the education distribution average somewhat fewer children.

Estimates that take account of unobserved common determinants of marriage, fertility, and child’s education differ substantially from those that ignore unobserved factors. The multi-equation effect of mother’s educational attainment on fertility is monotonically decreasing, ranging from approximately 4 children for women with no formal schooling to 1.5 children for women with post-secondary schooling (Figure 2). Husband’s education has an equally strong positive effect, ranging from less than 2 children for men with no education to nearly 5.5 children for men with post-secondary education. The big differences between the models in the estimated effects of educational attainment on fertility suggest that education differentials in fertility reflect a complex mixture of effects, including ability to afford larger families, aspirations for child quality, and the opportunity costs to women of high fertility (e.g., Becker 1991). The positive effect of husband’s schooling and negative effect of women’s schooling in the multi-equation model suggest that education differentials reflect a positive income effect for husbands and a negative opportunity cost effect for their wives.

The educational attainments of both mothers and fathers both have strong positive effects on the attainment of their children. In the model that does not take account of unobserved common determinants of marriage, fertility, and intergenerational transmission, mothers and fathers have approximately equal effects (see Table 3 and Figures 4 and 5). When unobserved factors are controlled, however, the estimated effects of mother’s educational attainment are greatly enhanced, whereas the estimates for the father’s effect are largely unchanged (Table 4).
These results suggest that conventional estimates of the effects of mother’s educational attainment may be subject to a large selectivity bias when unobserved determinants of marriage and fertility are not taken into account. Highly educated women who have many children are able to provide more advantages than their more poorly educated counterparts. These women, however, cannot do as much for their children than the average highly educated woman in the population, who has few if any children but could provide even greater advantages to the children that they do have.

**Simulations**

We assess the possible effects of women’s education on the educational attainment of the next generation through a variety of simulations. Each simulation is based on a set of random draws of 5 percent of IFLS married women, subject to assumptions about the specific change in the women’s education distribution, about whether fertility and/or marriage are taken into account, and about whether women-specific unobserved heterogeneity is taken into account. As discussed above, the simulations are based on the estimated parameters of our single and multi-equation models, which yield predicted husbands’ and children’s education distributions and numbers of children born. Simulations based on the multi-equation models also incorporate estimates of woman-specific random effects that are estimated for each of the three equations. We simulate the “effect” of women’s schooling by computing the expected offspring education distribution under six scenarios for women’s educational attainment:

1. Sample education distribution for adult women
2. Five percent of sample women are drawn from education category 1 and reassigned to category 2 (the other 95 percent retain their sample values)
3. Five percent of sample women are drawn from education category 2 and reassigned to category 3 (the other 95 percent retain their sample values)
4. Five percent of sample women are drawn from education category 3 and reassigned to category 4 (the other 95 percent retain their sample values)
5. Five percent of sample women are drawn from education category 4 and reassigned to category 5 (the other 95 percent retain their sample values)
6. Five percent of sample women are drawn from education category 1 and reassigned to category 5 (the other 95 percent retain their sample values)
Simulations 2-5 each move 5 percent of the sample one education level beyond their observed level, for each education transition separately. Simulation 6 moves five percent of the sample from the lowest to the highest education category. We standardize each expected education distribution to the sample average fertility level and compute the ratio of expected numbers of children in each education category for each of simulations 2-6 to the children in the respective category predicted by the observed women’s education distribution (simulation 1). Each of these simulations is carried out four times, once for each of four combinations of processes:

1. intergenerational transmission only;
2. intergenerational transmission plus differential fertility;
3. intergenerational transmission plus educational assortative mating;
4. intergenerational transmission plus fertility plus educational assortative mating.

Effects estimated for process 1 correspond to conventional estimates of the effect of mothers’ schooling on offspring’s schooling based on the conditional joint distribution of parents’ and offspring’s schooling. Effects estimated for processes 2-4 modify conventional estimates by taking account of one or both of fertility and marriage.

Table 5 reports the ratios of expected to observed numbers of children in each education for each combination of processes for each simulation, based on both single and multi-equation models. The patterns of ratios for the single and multi-equation models are very similar, although the variations in effects are somewhat larger for the latter. Because the multi-equation estimates take fuller account of unobserved factors that may shift in distribution with changes in the educational composition of women, they are a better basis for simulation. Thus, we confine our discussion to these estimates. The top right panel of Table 5 shows the impact of a change in women’s educational attainment when only the conditional association between parents’ and offspring’s schooling is considered. Five percent shifts in numbers of mothers between adjacent categories of educational attainment redistribute offspring’s educational attainment upward. Shifts at the bottom of the women’s distribution result in small increases in attainment throughout the offspring’s schooling distribution. Shifts in the middle or top of the women’s distribution have larger effects at the top of the distribution but negligible effects at the bottom. These patterns result from the overall upward intergenerational educational mobility in Indonesia. If we take the more dramatic step of replacing five percent of women with no schooling with the same number of women who have post secondary schooling, we can see that
the intergenerational transmission model implies a 10 percent reduction in offspring with no schooling and a 20 percent increase in offspring with post secondary schooling.

In simulations that take account of both the conditional association between parents and offspring and also differential fertility, the estimated effects of changes in women’s schooling distributions change in important ways. The main effect of differential fertility is to dampen the positive effects of women’s educational attainment on the next generation. When women move to higher levels of schooling, their (potential) children benefit, but women are likely to have fewer of those children. Thus the expected numbers of offspring at the highest levels of schooling are markedly reduced by differential fertility, below the level that would be expected on the basis of intergenerational mobility alone. Indeed, because of the substantial negative effect of women’s schooling on fertility, an intervention that moved five percent of the female population from senior secondary to post-secondary schooling would reduce the relative number of offspring who attain senior secondary or post-secondary education and increase the relative number who have no or only elementary education. That is, the differential fertility effect completely offsets the effect of the conditional positive association between mother’s and offspring’s schooling.

Whereas differential fertility tends to dampen the effects of the benefits that educated mothers can afford their offspring, assortative mating tends, for the most part, to reinforce those beneficial effects. When the effects of educational assortative mating are combined with the intergenerational transmission effects mothers’ education, improvements in women’s educational status sharply increase the numbers of offspring in post secondary education. This effect is particularly pronounced when women are redistributed from junior to senior secondary or from senior secondary to post secondary education. Upward educational mobility, plus a tendency for Indonesian women to marry men with somewhat more schooling than themselves, are responsible for these effects.

When all three processes are combined, as shown in the bottom panel of Table 5, we can see the contributions of intergenerational transmission, fertility, and assortative marriage. Interventions that raise women’s educational attainment at the lowest part of the distribution have a beneficial effect on the offspring’s educational distribution. For these women, the benefits of an improved position in the marriage market reinforce the direct effects of educational attainment per se, whereas fertility reductions from improved education are too

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7 These estimates are the effects of mother’s educational attainment controlling for father’s educational attainment.
modest to offset the marriage and transmission effects. At the higher levels of the educational distribution, in contrast, the benefits to women of improved marriage prospects, as well as the effects of intergenerational transmission are completely offset by the differential fertility effect.

7. SUMMARY AND CONCLUSIONS

How one views the effects of family background on socioeconomic attainment depends on how one thinks about assessing the consequences of changing the characteristics of individuals’ families of orientation. Many real or hypothetical interventions that may affect the socioeconomic characteristics of parents – especially those that change the educational attainments of mothers or fathers – occur relatively early in parents’ lives. Early interventions affect parents’ fertility and marriage as well as the attainments of their offspring. But interventions that affect fertility and marriage cannot be adequately assessed from observations of parent and offspring socioeconomic characteristics. If a change in women’s educational attainments changes their fertility and marriage behavior, then this alters the relative numbers of children in the offspring destination born to women from varying education levels and this, even in the absence of change in the family and individual level effects of mother’s schooling on offspring’s schooling, changes the distribution of schooling in the offspring generation. Our models take account of these features of intergenerational effects and reveal how the various components of intergenerational change contribute to the total effect of the educational attainment of a population of women on the education of the next generation.

An important feature of our models of marriage, fertility, and intergenerational transmission is that they take account of unobserved heterogeneity within categories of women’s measured educational attainment that is correlated across these three processes. When this heterogeneity is taken into account, the often noted concave pattern of education differentials in Indonesian fertility resolves into sharp negative and positive fertility gradients with women’s and men’s educational attainments respectively, suggesting that fertility is sharply governed by both opportunity cost and resource constraints on families. Of greater significance for the study of educational mobility, we find a large downward selectivity bias in conditional estimates of the effects of mother’s schooling on the educational attainment of offspring. When unmeasured heterogeneity is controlled, mother’s schooling has a much larger estimated effect on offspring, suggesting that differential fertility limits the number of children born to those women most
capable of helping their offspring achieve high levels of schooling. Our findings suggest that, in some populations, the beneficial effects of raising women’s schooling may be considerably greater than others have argued (for example, Behrman and Rosenzweig 2002).

The effects of women’s educational attainment on the next generation are more complex than a conventional analysis of mother-offspring educational mobility reveals. Positive educational assortative mating tends to reinforce the beneficial effects of increased women’s schooling. Women who obtain more schooling provide better environments for their children both directly and indirectly through their marriage to better educated men. At higher levels of educational attainment, however, the dampening effects of education on women’s fertility tend offset the beneficial effects of marriage and women’s education itself on the next generation. Thus, the long run effects of interventions to raise women’s schooling may depend on where in the education distribution these efforts are applied. Interventions among the most poorly educated women appear to be an unalloyed benefit for both the current and future generation. Interventions among better educated women may benefit them directly but have a limited or even negative effect on the education distribution of the next generation.

Unlike more conventional models of intergenerational transmission, our approach to the assessment of intergenerational effects is suitable for assessing the long run, intergenerational consequences of interventions in the lives of teenagers and young adults. In low education populations, which still characterize large parts of the developing world and immigrant populations in the developed world, efforts to increase educational attainment of women continues to be a promising avenue of human betterment. The models presented in this paper may prove to be a good way to quantify these effects.

In addition to their descriptive and practical value, these models are a foundation for dynamic empirically-based models of intergenerational reproduction, especially suitable for social traits that are not subject to severe supply constraints (Mare 1996, 2001). These models advance mobility studies beyond a static focus on who gets ahead to a more dynamic view of how populations and societies evolve.

8. POSTSCRIPT: ONGOING WORK

This draft is a progress report on our ongoing work. We plan to extend the analyses reported here in a number of ways:
Augmenting the IFLS Sample. We will augment our IFLS samples by including older IFLS respondents as adult children in the intergenerational transmission equation, and use their retrospective reports of parents’ educational attainments and sibship size. These observations, however, will not be useful for studying marriage or fertility because their mothers overrepresent married and high fertility women and provide no information about childless women.

The Decision to Marry. Whereas the analyses reported in this paper focus only on married women, a more encompassing model should also incorporate the decision to marry. Although virtually all Indonesian women marry average age at marriage has increased and, in other populations, many women fail to marry or marry late in their reproductive years, patterns that are often education-related.

Relaxing Parametric Assumptions. We will conduct sensitivity tests to show that our results do not depend on the parametric assumptions. This includes estimating multinomial rather than ordinal logit models for marriage and intergenerational transmission, allowing for mother-father interaction effects in the fertility and intergenerational transmission equations (although our preliminary investigations indicate that these are negligible), and using discrete mixture rather than multivariate normal models for unobserved common determinants of marriage, fertility, and intergenerational transmission.

Bootstrapping Simulation Effects. The analyses presented in this paper present the simulated effects of women’s educational attainment as population parameters, when in fact they are sample statistics. We will compute bootstrapped standard errors for our estimates.

Three-Level Models for Intergenerational Effects. Because many female IFLS respondents have multiple adult children, this affords the possibility of estimating a three-level model: (1) women, (2) processes within women, and (3) children within the transmission process. If we take account the additional variance component attributable to the clustering of children within the transmission process, it may be possible to obtain a better estimate of the intergenerational effect of women’s schooling.

Sex-Specific Effects. Our future analyses will examine the possibility of distinct effects of mothers and fathers on their daughters and sons (e.g., Thomas 1994; Mare and Chang 1998). This will show the intergenerational impact of changing women’s schooling on the difference in the education distributions of males and females.

Multi-Generational Effects. We will examine the multigenerational effect of changes in the distribution of women’s educational attainment. This will extend the aggregate analyses
reported by Mare (1996; 1997) and show the impact of observed and unobserved heterogeneity on education distributions in the long run.

*Sibship Size Effects.* We will include the effects of sibship size on the educational attainment of adult offspring. Because fertility is endogenous to the model, this lets us estimate the effect of a change in mother’s educational attainment that results from a change in the distribution of sibship sizes and the family level effect of sibship size on offspring’s attainment.

*Measurement Error in Proxy Reports.* The IFLS provides both self and proxy reports of many measures of educational attainment. For example, young adults report their parents’ educational attainments and, in many cases, these parents are also respondents who provide self reports. In other cases only proxy reports are available, such as when respondents whose parents were not respondents supply proxy reports of parental schooling. Although the latter reports may be unreliable, we will adjust for unreliability using observations where both self and proxy reports are available. This will enlarge our sample without compromising data quality.

*Fertility and Marriage Timing.* The model of intergenerational reproduction used in this paper ignores the age pattern of fertility and marriage. We investigate the effects of differentials in fertility levels but not fertility timing. We will incorporate age-specific fertility and marriage into the model. Apart from enabling us to investigate both timing and level effects, looking at age-specific fertility and marriage lets us use the fertility and marriage data of younger women who have not completed their childbearing or whose cohorts have not completed their transition into marriage. This will increase our sample size.

*The Indonesian Demographic Transition.* The decline in fertility, the increase in average educational attainment, and the reduction in sex differences in educational attainment are key aspects of the Indonesian demographic transition. We will apply our model to the demographic history of Indonesia over the past half century to see how well the predictions of the model track trends in fertility and education distributions.

*Two-Sex Models.* We will develop two-sex versions of the models presented here to obtain a symmetrical view of the effects of changes in men’s and women’s education distributions. The two-sex models will build on prior efforts by Mare (2000) at developing aggregate two-sex models of educational assortative mating, fertility, and intergenerational mobility.
REFERENCES


Thomas, Duncan. 1994. “Like Father, Like Son; Like Mother Like Daughter: Parental Resources and Child Height.” *Journal of Human Resources* 29: 950-88.
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# Observations 3963 3963 3963 3963 3611 3611 3611 3611 3611
Table 2. Distribution of Outcomes by Women’s Educational Attainment

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Table 3. Parameter Estimates for Single-Equation Model of Marriage, Fertility, and Intergenerational Transmission

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<td>4.0</td>
<td>2.424</td>
</tr>
<tr>
<td>Post Secondary</td>
<td>0.094</td>
<td>1.7</td>
<td>3.477</td>
</tr>
<tr>
<td><strong>Intercept</strong></td>
<td>1.247</td>
<td>71.1</td>
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</tr>
<tr>
<td><strong># Observations</strong></td>
<td>3963</td>
<td></td>
<td>3963</td>
</tr>
<tr>
<td><strong>Log Likelihood</strong></td>
<td>-3790.5</td>
<td></td>
<td>-10642.8</td>
</tr>
<tr>
<td>(Combined)</td>
<td></td>
<td></td>
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</tbody>
</table>

*Cutpoint parameters are not shown
### Table 4. Parameter Estimates for Multi-Equation Model of Marriage, Fertility, and Intergenerational Transmission

<table>
<thead>
<tr>
<th></th>
<th>Husband's Schooling (Ordered Logit*)</th>
<th>Children Ever Born (Poisson)</th>
<th>Offspring's Schooling (Ordered Logit*)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\beta$</td>
<td>$\beta$/S.E.($\beta$)</td>
<td>$\beta$</td>
</tr>
<tr>
<td>Women's Education (vs. None)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Elementary</td>
<td>2.736</td>
<td>27.3</td>
<td>-0.214</td>
</tr>
<tr>
<td>Junior Secondary</td>
<td>5.347</td>
<td>33.3</td>
<td>-0.331</td>
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<tr>
<td>Senior Secondary</td>
<td>6.932</td>
<td>38.6</td>
<td>-0.659</td>
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<tr>
<td>Post Secondary</td>
<td>8.538</td>
<td>26.0</td>
<td>-1.080</td>
</tr>
<tr>
<td>Husband's Education (vs. None)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Elementary</td>
<td>0.493</td>
<td>7.4</td>
<td>1.034</td>
</tr>
<tr>
<td>Junior Secondary</td>
<td>0.779</td>
<td>7.0</td>
<td>1.984</td>
</tr>
<tr>
<td>Senior Secondary</td>
<td>0.941</td>
<td>7.0</td>
<td>2.687</td>
</tr>
<tr>
<td>Post Secondary</td>
<td>1.127</td>
<td>6.4</td>
<td>3.990</td>
</tr>
<tr>
<td>Intercept</td>
<td>0.041</td>
<td>20.8</td>
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<tr>
<td>Variance of Random Effect</td>
<td>1.000</td>
<td>0.436</td>
<td>0.436</td>
</tr>
<tr>
<td>Covariances</td>
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</tr>
<tr>
<td>Husband's Schooling - Fertility</td>
<td>-0.451</td>
<td>-6.5</td>
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<tr>
<td>Husband's Schooling - Offspring Schooling</td>
<td>0.772</td>
<td>4.8</td>
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</tr>
<tr>
<td>Fertility - Offspring Schooling</td>
<td>-0.100</td>
<td>-1.6</td>
<td></td>
</tr>
<tr>
<td># Observations</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Women</td>
<td>3963</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Outcomes</td>
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<tr>
<td>Log Likelihood</td>
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<td>-17326.1</td>
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</table>

*Cutpoint parameters are not shown
Table 5. Ratios of Simulated to Observed Offspring’s Schooling Distributions

<table>
<thead>
<tr>
<th>Simulation</th>
<th>None to Elem</th>
<th>Elem to Jr Sec</th>
<th>Jr Sec to Sr Sec</th>
<th>Sr Sec to Post Sec</th>
<th>None to Post Sec</th>
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</thead>
<tbody>
<tr>
<td><strong>Transmission Only</strong></td>
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<tr>
<td>Single Equation</td>
<td>0.952</td>
<td>0.979</td>
<td>1.010</td>
<td>1.020</td>
<td>1.010</td>
</tr>
<tr>
<td>Multi-Equation</td>
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<td>0.960</td>
<td>1.023</td>
<td>1.033</td>
<td>1.008</td>
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<tr>
<td><strong>Transmission + Fertility</strong></td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Single Equation</td>
<td>0.952</td>
<td>0.979</td>
<td>1.010</td>
<td>1.020</td>
<td>1.010</td>
</tr>
<tr>
<td>Multi-Equation</td>
<td>0.930</td>
<td>0.961</td>
<td>1.018</td>
<td>1.031</td>
<td>1.017</td>
</tr>
<tr>
<td><strong>Transmission + Marriage</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Single Equation</td>
<td>0.952</td>
<td>0.979</td>
<td>1.010</td>
<td>1.020</td>
<td>1.010</td>
</tr>
<tr>
<td>Multi-Equation</td>
<td>0.909</td>
<td>0.941</td>
<td>1.025</td>
<td>1.054</td>
<td>1.013</td>
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<tr>
<td><strong>Transmission + Fertility + Marriage</strong></td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Single Equation</td>
<td>0.952</td>
<td>0.979</td>
<td>1.010</td>
<td>1.020</td>
<td>1.010</td>
</tr>
<tr>
<td>Multi-Equation</td>
<td>0.917</td>
<td>0.947</td>
<td>1.026</td>
<td>1.057</td>
<td>1.029</td>
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</table>
Figure 1. Husbands' Education Given Wives' Education*

*Random intercept held at 0 in 3-equation estimates
Figure 2. Expected Fertility by Mothers' Education
(Fathers' Education held at Elem)*

*Random intercept held at 0 in 3-equation estimates
Figure 3. Expected Fertility by Fathers' Education
(Mothers' Education held at Elem)*

*Random intercept held at 0 in 3-equation estimates
Figure 4. Children's Education Given Mothers' Education
(Fathers' Education held at Elem)*

*Random intercept held at 0 in 3-equation estimates
Figure 5. Children's Education Given Fathers' Education
(Mothers' Education held at Elem)*

*Random intercept held at 0 in 3-equation estimates.
Figure 6. Effects of Redistributing Five Percent of Women from Senior Secondary to Post Secondary Education
Figure 7. Effects of Redistributing Five Percent of Women from No Education to Post Secondary Education

Ratio of Simulated to Observed Children's Education

Children's Education
- trans
- trans_fert
- trans_marr
- tr_fert_marr