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Effect Pathways of Informal Family Separation on Children's Outcomes: Paternal Labor Migration and Long-term Educational Attainment of Left-Behind Children in Rural China

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Keywords

family separation, educational attainment, China, left-behind children, paternal labor migration, father absence

Disciplines

Asian Studies | Education | Family, Life Course, and Society | Inequality and Stratification | International and Comparative Education

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Informal family separation due to parental labor migration is an increasingly common experience in the lives of children in many countries. This paper proposes a framework and method for analyzing "effect pathways" by which parental labor migration might affect children's outcomes. The framework incorporates home-environment and child-development mechanisms and is adapted from migration, sociology of education and child development literatures. We test these pathways using data on father absence and long-term educational outcomes for girls and boys in China. We apply structural equation models with inverse probability of treatment weighting to data from a 15-year longitudinal survey of 2,000 children. Significantly, fathers' migration has distinct implications for different effect pathways. It is associated most significantly with reduced human capital at home, which has the largest detrimental effect on children's educational attainment, among those studied. At the same time, father absence is associated with better family economic capital and mothers showing more parental warmth, which partially buffer the negative implications of father absence. Overall, father absence corresponds to a reduction of 0.364 years on average in children's educational attainment, but the reduction is larger for boys than for girls. For boys and girls, the reduced availability of literate adults in the household linked to father absence is an important effect pathway. For girls, this detrimental effect is partially offset by a positive income effect, but for boys, no such positive effect is observed.

Introduction

Informal family separation due to parental labor migration is an increasingly common experience in the lives of children in many countries. Globally, it is estimated that hundreds of millions of children are left behind due to parental migration or absence,[1] and this number continues to grow (Fellmeth et al. 2018). The immense scale of the left-behind phenomenon has prompted intense academic scrutiny, with numerous scholars investigating the problems faced by left-behind children. Yet, findings are surprisingly mixed regarding how these children fare (Wen et al. 2015; Liang 2016; Adams, Cuecuecha, and Page 2008; Arguillas and Williams 2010). A critical reason for these mixed findings is that parental migration, in principal, may carry distinct implications in the different domains of the home environment that contextualize children's education and development. For example, migration may lead to greater material resources in the household through remittances – resources that can be ensure in a child's access to education (Carling, Menjívar, and Schmalzbauer 2012, 193) – but lower "social capital" if parental supervision or assistance with homework decreases. However, we know little about the mechanisms linking parental migration to outcomes, because most of the literature investigates gaps in outcomes associated with parental absence, without specifying pathways of influence.

In this paper, using the case of China, we propose an approach for investigating the long-term educational implications of parental absence for children, with an emphasis on "effect pathways" or mechanisms linking parental absence in childhood to long-term educational outcomes. We capitalize on availability of information about father absence in a 15-year longitudinal data collection project that followed rural children and their families from 100 villages in Northwest China. We combine Liang's "resource generation model" and "family disruption model" of parental migration (Liang 2016) with a framework for analyzing children's home environments grounded in human, social, and cultural capital theories in sociology of education. We do this by identifying elements of children's home environments that are likely to be affected by parental migration and that fit within established theoretical frameworks for analyzing educational reproduction and mobility. We also investigate the potential implications of parental absence and home environment effects via children's own developmental outcomes at the time of parental absence – academic performance and behavioral problems. Finally, we address the possibility that father absence has different implications for boys' and girls' educational attainment.

To address concerns about selectivity of labor migration, we apply structural equation models with inverse probability of treatment weighting, in which father absence is defined as the treatment. We operationalize "effect pathways" of parental absence as pathways through which parental absence has a significant effect on a mediator that, in turn, has a significant effect on long-term educational outcomes. In this way, we are able to consider both positive and negative implications of absence via different mediation pathways, and we are able to quantify the size of the total effect of absence attributable to each effect pathway.

[1] Parental absence refers to the status of parent(s) being absent from home due to migration. Children who move with their migrant parents are not included in this paper. In this sense, we use parental absence and parental migration interchangeably, both of which mean children are left behind at home by their migrant parent(s).

Theoretical Framework and Research Questions

Many scholars have examined the educational and developmental consequences of parental migration or absence for children, but findings are mixed. For example, some scholars argue that left-behind children benefit from increased family income, which leads to better educational outcomes (e.g., Hadi 1999; Jones and Kittisuksathit 2003). Other studies find that the changes in family structure and the absence of parental involvement due to parental migration have negative effects on children's educational outcomes (e.g., Meng and Yamauchi 2017; Jampaklay 2006). For instance, a study analyzing the Mexican Family Life Survey and the Indonesian Family Life Survey finds that parent's internal migration and international migration both play a negative role in children's education, although the effect size varies (Lu 2014). However, there are also studies showing that paternal migration does not play a major role in determining children's educational outcomes (e.g., Antman 2012; Ren and Treiman 2016; Xu and Xie 2015; Lu 2012). The inconsistent empirical findings about parental migration and children's outcomes may be explained by a variety of differences across studies, such as the origin and destination of migration, the age and gender of left-behind children, the gender of migrant parent, and the time of migration, among others. But in explaining positive or negative results, authors often resort implicitly or explicitly to two competing theoretical frameworks: the resource generation model and the family disruption model (Liang 2016).

The resource generation model posits that parental migration has positive effects on home environment, brought about by improved economic resources. There is good reason to believe, in some contexts, that this might be the case. For example, existing literature in China estimates that remittances constitute about 20% of total incomes in migrant households (Fan 2008). One study in South Africa shows that remittances from migrant parents substantially increase children's school attendance and household educational spending, which ameliorates educational inequality among children (Lu and Treiman 2011).

The family disruption model, in contrast, posits that parental absence in childhood may reduce both the quantity and quality of social, emotional, and intellectual stimuli for children, which ultimately leads to adverse child developmental outcomes (Parreñas 2005; Dreby 2010). One key mechanism could be described as human capital loss in the household. Parental human capital plays a key role in children's development (Brown 2006; Zhao and Glewwe 2010), and parental migration means the loss of parental human capital for left-behind children during the period of parental absence. In concrete terms, in poor rural regions, the absent parent or parents may be the most educated adults in the household, and their temporary loss may leave children without a source of mentorship or advocacy when educational challenges arise. However, the extent to which the loss of parental human capital affects left-behind children's long-term educational outcomes remains unclear.

Related to the human capital loss mechanism, social capital is a critical domain of home environment in the sociology of education literature that could be affected by parental absence. Parental migration is associated, in some studies, with a lack of parental involvement, schoolwork supervision, and emotional support for left-behind children (Hannum et al. 2018; Liang 2016). There is also evidence supporting contradictory results. For example, some research suggests that for families with only one parent absent, the stay-at-home primary caregiver (usually the mother) may tend to compensate with higher levels of parental warmth or support toward children (Chen et al. 2019).

Cultural capital, variously defined, is another dimension of household context that is crucial for children's educational outcomes (De Graaf, De Graaf, and Kraaykamp 2000; DiMaggio 1982; Lareau and Weininger 2003; Bourdieu 1986). In survey-based work, the operational definition of cultural capital may include the number of books and magazines, book-reading behaviors, extracurricular activities, and art participation, depending on social contexts and research topics (DiMaggio and Mukhtar 2004; Lareau and Horvat 1999). One study shows that there are substantial social class differences in book-reading behaviors among children in urban China (Wang et al. 2006). Research also shows that migrant children tend to have limited cultural resources, which constrains their access to local resources and services (Sime and Fox 2015). However, how cultural capital is associated with educational outcomes for left-behind children in rural areas is rarely studied.

Parental absence may be associated with differences not only in home environment, but also in children's immediate, individual developmental outcomes. A large body of literature has examined the deleterious effects of parental absence on left-behind children's emotional and behavioral problems (F. Fan et al. 2010; Qin and Albin 2010; Adhikari et al. 2014). For instance, a cross-country comparative study in Africa finds that parental migration has negative effects on left-behind children's psychological well-being (Mazzucato et al. 2015). A review of the literature on father absence in the United States, which is admittedly tied more to non-marital childbearing or family dissolution rather than migration, suggests that father absence is closely linked to socio-emotional development problems and particularly to greater externalizing problems (McLanahan, Tach, and Schneider 2013, 17). The implications of family disruption may be different for girls' and boys' socioemotional development (for a recent critical review, see Brenøe and Lundberg (2018)).

Finally, existing literature also evaluates the short-term effects of parental absence on left-behind children's academic performance, with inconsistent findings. For example, a study using data from the 2007 and 2009 Young Lives surveys shows that parental migration is linked to lower cognitive-ability test scores in India and Vietnam (C. V. Nguyen 2016). But another study examines the impact of parental migration on children's academic performance in China using a pre- and post-parental migration comparison design, and suggests a positive effect of parental migration on English test scores (Bai et al. 2018). These studies suggest certain key short-term impacts of parental absence, but the long-term implications of these short-term child developmental outcomes for children's educational attainment are rarely studied.

There are at least three major limitations in current literature. First, existing studies only focus on one or two mechanisms (implicitly using either a resource generation model or family disruption model) by which parental absence affects educational outcomes, such as the improvement of economic resources (Nguyen et al. 2006) or the lack of parental supervision (Lu 2012). This limitation not only hinders the understanding of how parental absence affects educational outcomes, but may also lead to omitted variable bias – omitted mechanisms may be the true reasons for the detected effects. Second, each of the current studies only explores a small part of the diverse domains of home environment and child development, and thus different studies find different and sometimes opposing effects of parental absence. Without a simultaneous examination of diverse home-environment and child-development mechanisms of impact or effect pathways, we can neither calculate the overall effect of parental absence nor evaluate the relative importance of a specific impact. Finally, most studies stop at only revealing the short-term consequences of parental absence but fail to link these short-term consequences to children's long-term developmental outcomes. Thus, whether the positive or negative impacts of parental absence are merely temporary or have longstanding implications is still unknown.

Given these limitations, we propose a framework to analyze the long-term implications of parental absence for children's educational attainment via distinct mechanisms. The framework synthesizes both the resource generation model and the family disruption model and incorporates diverse home-environment and child-development mechanisms. Home environment contains four domains: economic capital, human capital, social capital, and cultural capital. Child development comprises two short-term indicators: cognitive skills and non-cognitive skills.

Our theoretical framework is depicted in Figure 1. In this framework, father absence may have a direct impact on children's educational attainment over time. More importantly, father absence affects home environment and child development, both of which further affect educational attainment. Moreover, home environment can also influence the short-term outcomes of child development. It should be noted that different home-environment and child-development mechanisms are not isolated but correlated, which for the simplicity of presentation is not shown in Figure 1 but is included in our analytic models.

(Figure 1)

To our knowledge, the current paper is the first to adopt a framework that links the resource generation and family disruption models in the migration literature to critical domains of child home environment drawn from the sociology of education literature. The paper incorporates short- and long-term influences of parental absence, allows for connections between different mechanisms, facilitates the identification of multiple pathways linking father absence to educational attainment, and enables calculation of the relative importance of each effect pathway. Guided by this framework and capitalizing on a 15-year longitudinal study of children in China, we pose three questions: First, is parental absence in childhood associated with children's long-term educational attainment? Second, what are the most significant pathways that link parental absence to children's educational attainment? Finally, given both the history of son preference in China and literature elsewhere (e.g., Brenøe and Lundberg 2018) suggesting that girls and boys may be differently vulnerable to family disruption, we pose a third question: are there gender differences in the overall association or in the particular pathways linking parental absence and children's long-term educational attainment?

The China Context

In 2010, 61 million children in China were left behind by one of their parents – 21.88% of China's children and nearly the total number of children in the United States in 2010 (All China Women's Federation and National Bureau of Statistics of China 2016; Zhou et al. 2014). The massive number of left-behind children in China is a product of two phenomena: first, the decision of increasing numbers of rural residents to move into cities for work and, second, the decision of migrants not to bring children with them. The first of these phenomena can be credited to a shift from a collective, planned economy to a private, market economy. This economic shift initiated in 1978, and over time reduced state control over labor mobility (Chang et al. 2011). The second of these phenomena can be traced to persisting policy barriers that ban or limit migrant workers' children's access to education in destination cities. These barriers have meant that with rising numbers of migrant workers has come a rising number of children left behind.

Data and Methods

Data

To answer the three questions listed in the preceding section, we analyze data from the 2000 and 2015 rounds of the Gansu Survey of Children and Families (GSCF, 2000, 2015), a longitudinal study of 2,000 children in 100 rural villages in China's Northwest. The sample drawn was a multi-stage cluster sample of rural households with children in the target age range. The children were first interviewed at ages 9 to 12 in the year 2000 and last interviewed in early adulthood in the year 2015. The initial questionnaires were administered at schools and in homes to children, teachers, school principals, mothers, and household heads. By the year 2015, all children should have finished formal schooling and thus finalized their educational attainment. In 2015, 1,613 now-adult children of the initial sample were successfully followed up. Although the GSCF is not nationally representative, the unique 15-year timespan makes it the sole dataset on child development in China that can link childhood experiences with adulthood outcomes.

We focus on data collected in 2000 and 2015 for this study. GSCF collected data also in 2004, 2007, and 2009. The 2007 wave focused on target children's siblings and the 2009 wave focused on target children's employment and educational outcomes, both of which did not include the measures of different home-environment and child-development mechanisms examined in this study. The 2004 wave was similar to the initial wave which contained the measures of most mechanisms examined in this study. However, in 2004, 9.65% of sampled children dropped out of school and 6.45% were missing on enrollment status. No longer being in school, these children (16.10%) had no observable educational achievement in 2004. Since educational achievement is a key mechanism through which home environments affect educational attainment, those cases without educational achievement in 2004 could only be dropped, because the lack of educational achievement is different from missing values and cannot be handled by the missing value techniques. This step would reduce the analytical sample size to 1,678. As the method employed in this study (structural equation modeling, as discussed in the following section) requires a large sample size for efficient and unbiased estimates (Kline 2015), the reduced sample would have greatly diminished the power of this study. For this reason, we did not include the 2004 data.

In addition, parental migration status in 2004 did not differ significantly from that in 2000. In 2004, 98.35% of mothers stayed at home and only 8.83% of resident fathers in 2000 became migrants in 2004, which provided too few cases to do within-family comparison to trace the changes in family context due to parental absence. Moreover, our research goal is not to trace temporal changes in parental absence, but to identify diverse possible mechanisms linking parental absence in childhood to long-term educational attainment. Thus, the use of the first and last rounds of data collection can fulfil our research goal.

Measurement

Educational Attainment and Father Absence

The key dependent variable in this study is children's educational attainment. In the 2015 survey, respondents were asked about their highest degree of education attained. Based on their responses, we generate a continuous measure of total years of education attained, with an average of 11.387 years.[2] Since the measure of educational attainment in 2015 had many missing values, we use the years of education completed in 2009 as an auxiliary variable – a variable used for improving the procedure of handling missing data but not included in the analytical model. The auxiliary variable can be correlated with the educational attainment measurement that have missing values, regardless of its correlation with the mechanism of missingness (Collins, Schafer, and Kam 2001). In a longitudinal study, an ideal auxiliary variable is often the same variable measured at a different time point, given the strong dependence or correlation between these two measures (Collins, Schafer, and Kam 2001). The average years of educational attainment in 2009 was 9.527 years, and its correlation coefficient with educational attainment in 2015 was 0.727, which suggests it is a good auxiliary variable.

All variables other than educational attainment were measured in the year 2000. In the 2000 baseline survey, parents were asked about the months of residence at home during the last year. When defining parental absence, the current literature usually adopts six months of absence as the criterion (De Brauw and Mu 2011; Graham and Jordan 2011; Nguyen 2016; Sun and Wang 2016). Following this rule, parents who lived at home for six months or fewer during the last year (i.e., absent for at least six months) were defined as being absent. According to this definition, 19.6% of children were father-absent while only 1.7% of children were mother-absent in the year 2000. Because of the extremely low proportion of mother absence in 2000, we focus exclusively on father absence.

Home Environment

We evaluate four domains of home environment in the year 2000: economic capital, human capital, social capital, and cultural capital. Economic capital was measured by family income per capita – the total family income during the last year from different sources (wages, farm and forest production, livestock farming, and self-employment) divided by family size. Human capital was measured by the number of adults (parents, uncles, aunts, and grandparents) *present*

[2] In Shen, Hu, and Hannum (2017) which used the same dataset, the average of educational attainment was 11.24 years. This slight difference in the average results from different coding strategies for the degree category "secondary trade school/technical school/vocational high school". The time required for a degree in secondary trade school/technical school/vocational high school ranges from 2 years to 3 years, and thus the total years of education for this category also varies from 11 to 12 years. Shen, Hu, and Hannum (2017) adopted the minimum years which distinguished this category from "high school" (12 years), while in this paper we adopted the maximum years which is consistent with the coding strategy used in another dataset – the China Family Panel Studies (Xie et al. 2012).

in the home with reading ability. Thus, a father at home contributes a “1” to this measure if he is literate and a “0” if not. Representing a human capital loss associated with migration, a literate yet absent father contributes a “0”.

Social capital consisted of two parts: “parental warmth” and “parents or other adults at home doing things together with children”. Parental warmth usually represents parental support and care, including encouragement, positive reinforcement, active involvement in children's lives, and appropriate monitoring (Pettit et al. 1997). In this survey, it was a summative scale of 18 items such as “your parents encourage you to think independently” or “your parents are always gentle with you”. These 18 items were answered by children on a 3-point Likert scale (1 to 3: never, sometimes, often) with a higher score indicating more parental support. The Cronbach’s alpha for the parental warmth scale was 0.77. Parents or other adults at home doing things together with children was measured by the 5 following activities: reading story books, helping with assignments, playing games, going to bookstores, and discussing things that children were interested in. Children indicated the frequency (1 to 3: never, sometimes, often) of each activity with a higher score meaning more frequent. These five items were combined into a single scale, for which the Cronbach’s alpha was 0.70. The last aspect of home environment – cultural capital – was denoted by the number of books that children had, including schoolbooks, magazines, and other books. All of the home environment variables were measured in the year 2000, when father absence had occurred.

Child Development

We explore two categories of child development: cognitive skills and non-cognitive skills. As an indicator of cognitive skills, children’s educational achievement is denoted by the average of teacher-reported Chinese and math grades in the preceding semester, both measured with a scale from 0 to 100. Non-cognitive skills was measured by behavioral problems based on the widely-used Child Youth Self Report (Achenbach 1991), with two types of behavioral problems included: internalizing problems and externalizing problems. Internalizing problems are inner-directed behavioral problems such as withdrawal and anxiety, while externalizing problems are outer-directed behavioral problems that reflect children’s negative actions directed toward the external environment, such as delinquent and aggressive behaviors (Eisenberg et al. 2001). The Cronbach’s alpha scores were 0.82 for internalizing problems and 0.88 for externalizing problems, respectively. Just as for the home environment variables described above, all of these child development variables were measured in the year 2000, when father absence had occurred. Thus, the possible influences of father absence on child development variables were also captured in these measures.

Covariates in the Propensity Score Model

Variables included in the propensity score model should be those theoretically correlated with either the outcome (educational attainment) or both the outcome and the treatment (father absence), no matter whether such correlations are statistically significant in the dataset (Wyss et al. 2013; Rubin and Thomas 1996; W. Leite 2016). Therefore, we include in the propensity score model the covariates of child demographics (age and gender), family structure (sibship size), children’s education and health, and the household’s economic, cultural, and social capital.

Children's education was a binary indicator of retention experience in the period from first grade to one year prior to father absence. Children's health was denoted by a binary variable of diagnosed chronic disease in the past. We measure family economic capital by the value of fixed assets and durable goods in each household, which included 38 items such as cars and sewing machines, among others. Compared with income, the value of fixed assets and durable goods was a more reliable economic indicator prior to father absence. Family cultural capital was composed of father's and mother's years of education. Family social capital was measured by mother's evaluation of neighbor relationship in the village (1-3: not good, normal, very good). All these covariates were indicators prior to father absence and had no missing values. All the variables used in the propensity score model and the outcome model are summarized in Table 1.

(Table 1)

Method and Analytical Strategy

Structural equation modeling (SEM) with inverse probability of treatment weighting (IPTW) is utilized for analysis. Compared with conventional regression methods, SEM features the following advantages. First, its capability of simultaneously estimating different equations enables us to explore how father absence may affect educational attainment through different pathways – home-environment and child-development mechanisms. Second, it has a convenient and powerful technique of handling missing data, i.e., the full information maximum likelihood (FIML) method.[3] Third, the multiple group analysis in SEM can estimate the same model for different subgroups simultaneously, which facilitates the comparison between girls and boys for all of the parameters of interest. Given these advantages, SEM is our preferred method for investigating the long-term impacts of father absence on children's educational attainment.[4]

In addition, inverse probability of treatment weighting is employed to reduce selection bias. Inverse probability of treatment weighting creates a pseudo-population in which the distributions of confounders are the same for the treated and untreated groups, and thus there is no longer an association between confounders and treatment, which makes the crude association between treatment and outcome unconfounded (Funk et al. 2011; Greenland, Robins, and Pearl 1999; Liu et al. 2019). Compared with matching, two advantages of inverse probability of treatment weighting make it a better bias-reduction method for this study. First, it has the flexibility of allowing for almost any analytical model in the outcome analysis, such as SEM. Second, it keeps the original sample size without dropping the unmatched cases, which is particularly attractive for this study since SEM requires a larger sample size than conventional regression methods (Kline 2015). We use STATA 15 to estimate the inverse probability weights and SEM models.

There are four steps in our analysis. First, we begin with a baseline unweighted SEM regressing educational attainment on father absence. With this approach, we do not seek to reveal a causal

[3] Compared with conventional multiple imputation which uses two models (imputation model and analysis model) that may produce incompatibility, handing missing data in SEM with FIML method only uses one model – the real analysis model, which makes results unaffected by the imputation model, and the results are also asymptotically efficient (Allison 2015).

[4] SEM also has a goodness-of-fit test for the whole model. However, these goodness-of-fit test statistics are not available in STATA due to the use of village-clustered robust standard errors in this study.

link between father absence and educational attainment, but instead to display an overall picture of whether father-absent children are disadvantaged in educational attainment. The baseline model includes child demographics (age and gender) as control variables. Also, since educational attainment in 2015 has a relatively high proportion of missing values, a strong auxiliary variable – educational attainment in 2009 (correlation coefficient is 0.727) – is used to improve model efficiency and reduce estimation bias (J. Graham 2003). Following the typical use of an auxiliary variable, this auxiliary variable is modeled to be correlated with all other variables but not used in the model predicting educational attainment in 2015.

Next, we estimate the propensity score of father absence. In a multilevel research design, the reduction of selection bias due to clustering can be achieved by accounting for clustering effect in the propensity score model (Li, Zaslavsky, and Landrum 2013; W. L. Leite et al. 2015). Therefore, we use the random intercept multilevel logistic regression to estimate the propensity score of father absence. After the propensity score of father absence is estimated, an inverse probability weight is calculated for each case. To further reduce bias due to large and influential weights, we use the stabilized weights proposed by Robins, Hernán, and Brumback (2000). After obtaining the stabilized weights, we use father absence as the sole independent variable to run weighted linear regression (continuous covariate as the dependent variable) or weighted logistic regression (binary covariate as the dependent variable) to check data balance to ensure that weighing has removed data imbalance and corrected for selection (Guo and Fraser 2015).

Third, using the stabilized weights calculated in the second step, we conduct a weighted SEM analysis to identify distinct, significant pathways that link father absence to educational attainment. In this step, different aspects of home environment and child development, affected by father absence, serve as predictors of educational attainment. Therefore, except for child demographics, all covariates about family conditions utilized in the propensity score model are no longer included. This is consistent with the model specification suggestion that the outcome model and the propensity score model rarely have the same set of covariates (Freedman and Berk 2008; Guo and Fraser 2015). Moreover, village-clustered standard errors are used to adjust for dependence within each cluster (Primo, Jacobsmeier, and Milyo 2007; Cheah 2009). As in the baseline model, full information maximum likelihood and the auxiliary variable of educational attainment are also used to handle missing data for better model estimation (Allison 2015; J. Graham 2003).

In addition, home-environment and child-development mechanisms are not isolated but correlated. For instance, family economic capital as a critical component of family SES affects all other aspects of home environment and child development. In particular, economic capital may influence human capital for the reason that a family's economic capital determines the affordable number of cohabitants in the family, which overlaps with human capital measured by the number of adults at home with reading ability. Cultural capital, measured by the number of books, can be influenced by human capital – adults at home with reading ability (Jager and Breen 2016). Furthermore, one form of social capital – doing things together with parents or other adults at home – contains intellectual activities like reading story books and helping with assignments, which should also be affected by human capital at home. All aspects of home environment affect child development. Within the domain of child development, children's behavioral problems also have an impact on educational achievement. Moreover, items within the same category of a mechanism, such as the two forms of social capital and the two types of behavioral problems, are correlated with each other (i.e., their error terms are correlated in the model). Figure 2 describes the detailed specification of the model.

(Figure 2)

Finally, based on the model in the third step, we conduct a multiple group analysis to examine whether there are gender differences in the overall association and the specific pathways linking father absence and educational attainment.

We use full information maximum likelihood (FIML) to handle missing data. To adjust for data dependence, we use village-clustered robust standard errors for all analytical models. Due to the use of clustered standard errors, the goodness-of-fit test statistics are no longer available in STATA and thus not reported in this paper.

Results

Father Absence and Educational Attainment

Table 2 shows the results from the baseline model, which estimates the long-term association of father absence with children's educational attainment. After controlling for child demographics (age and gender), father-absent children have 0.510 years fewer total years of education attained. This finding suggests father absence in childhood has a non-trivial long-term negative association with children's educational attainment. We turn next to investigating mechanisms.

(Table 2)

Data Balance

Before the investigation of mechanism, we address the selectivity of migration by estimating the propensity score model first and calculating the stabilized inversed probability weights. Table 3 displays data imbalance before weighting and data balance after weighting. In this step, father absence as the sole independent variable predicts each covariate using bivariate linear regression or logistic regression. Before applying weights, all covariates are not significantly related to father absence, except for family economic capital – fixed assets and durable goods. This result suggests that father's labor migration is largely an economic decision based on prior family economic conditions: fathers from poorer families have a higher likelihood of absence or migration for work. After weighting, none of these covariates has a significant association with father absence and all their standard errors increase. This result indicate that weighting has successfully balanced our data.

(Table 3)

Significant Pathways Linking Father Absence to Educational Attainment

With data balance achieved, we apply the stabilized inverse probability weights to structural equation models depicted in Figure 2. The results are listed in Table A1 in appendix. To get a clear picture of the complex results shown in Table A1, we identify all the significant pathways linking father absence to children's educational attainment. We define a significant pathway as a pathway from father absence to children's educational attainment in which all coefficients are statistically significant at least at $p < 0.1$ level.[5] All the identified significant pathways are described in Table 4. Our model suggests that the measured effects of father absence are largely flowing through the significant indirect mechanisms – the effect pathways – specified in Table 4, which sum to an effect of just about over a third of a year (-0.364 years). With these pathways included in the model, father absence has no remaining significant direct impact on educational attainment.

Specifically, father absence is associated with more economic capital (family income per capita), which promotes educational attainment not only by itself but also through its direct impacts on human capital (adults at home with reading ability) and cultural capital (number of books) – the latter two's effects on educational attainment mainly operate through educational achievement. In total, the advantage in economic capital brought by father absence corresponds to a 0.140-year increase in educational attainment. In addition, the change in social capital (parental warmth) incurred by father absence contributes to a 0.048-year increase in educational attainment. This implies that when father is absent mother tends to show more parental warmth to children to offset the negative impacts of father absence (Chen et al. 2019).

Father absence also corresponds to a reduction of human capital at home. The loss in human capital due to father absence, in addition to directly reducing educational attainment, also reduces cultural capital (number of books) and educational achievement, both of which further lower educational attainment. In total, the loss in human capital due to father absence leads to a decrease of 0.552 years in educational attainment.

Putting these significant pathways together, we find that father absence in childhood is associated with 0.364 fewer years of educational attainment. Among all of the home-environment and child-development mechanisms, the loss in human capital has the largest detrimental effect (-0.552 years) on children's educational attainment – even the total positive effects (0.188 years) of economic capital and social capital can only offset about one third of such a large negative effect. One reason could be that in rural children's homes in China, fathers are usually the adult household members with the highest level of education. In our Gansu case, only 8.7% of households had more-educated mothers than fathers.[6] Therefore, father absence often means the loss of the most educated adult in the household, which can bring a substantial detrimental effect on children's educational attainment.

[5] Two reasons justify the use of the 0.1 alpha level. First, for a pioneering and holistic study, a relatively high alpha level helps uncover as diverse pathways as possible and also reduces the danger of just cherry-picking statistically significant results. Second, standard errors and p-values are sensitive to sample size. According to the N:q rule that defines the appropriate sample size for SEM (i.e., the ratio of the number of observations (N) to the number of model parameters (q)), the recommended sample size should have an N:q ratio of 20 (Jackson 2003; Kline 2015). The N:q ratio in our full model is 2,000:73, which is 27. Thus, although our sample is sufficient for research, it is not as large as the "big data" that can yield extremely small standard errors and p-values. In the latter case, a lower alpha level would be preferred.

[6] For 52.25% families, father had a higher level of education than mother did; and for 39.05% families, father and mother had the same level of education.

It is worth noting that in Table 4, a longer pathway (i.e., the one with more mediators) usually has a smaller effect size, which is normal since most mediators have smaller-than-1 coefficients. The effect size of a long pathway may also be statistical insignificant. But small effect size or statistical insignificance in Table 4 does not necessarily negate the possibility of a long pathway. As clarified in the preceding section, the identification of each pathway shown in Table 4 has already passed a series of significance tests (i.e., each coefficient on a pathway should be significant at least at $p < 0.1$). The additional significance test in Table 4 provides supplemental information to evaluate the effect size of each pathway, not to invalidate them. Moreover, these pathways provide needed insights about possible mechanisms linking parental absence to educational attainment, which may become more significant both practically and statistically in other studies using different datasets.

(Table 4)

Gender Differences

To examine whether there are gender differences in the overall association and particular pathways linking father absence and children's educational attainment, we conduct a multiple group analysis, which estimates results for males and females simultaneously. In this case, gender is no longer a control variable in the model. We first estimate an unconstrained model that allows gender differences in all parameters, and then a constrained model which assumes the structural coefficients (i.e., the effect of one variable on the other variable) are the same for males and females.[7] The likelihood-ratio test indicates that these two models are significantly different,[8] which suggests the unconstrained model (i.e., the gender-difference model) should be favored.

The specific effect pathways for males and females are summarized in Table 5 and the detailed results from the gender-difference model are appended in Table A2. Three main findings emerge. First, overall, father absence corresponds to a reduction in educational attainment of 0.517 years for boys and 0.338 years for girls, but only the reduction for boys is statistically significant. Second, for boys, there are no positive impacts to offset the detrimental impacts of human capital loss due to father absence. Third, the economic capital brought by father absence significantly benefits girls but not boys. On average, father absence leads to an increase of 0.270 years in girls' educational attainment through the gain in economic capital. In short, these results suggest that father absence hurts boys more than girls in terms of educational attainment.

(Table 5)

Discussion and Conclusion

In this paper, we propose a framework that allows for differential effects of migration on children's long-term outcomes via effects on the home environment and their immediate implications for child development. We apply structural equation models with inverse probability of treatment weighting to analyze data from the 2000 and 2015 rounds of the Gansu Survey of Children and Families (GSCF). Results show that father absence is negatively

[7] By default, the factor loadings are also constrained to be the same.
[8] The Chi-square statistic is 141.12 with 53 degree of freedom and the p-value is less than 0.001, which rejects the hypothesis that the constrained model is nested in the unconstrained model.

associated with children's long-term educational attainment. Most significantly, father absence is linked to reduced human capital at home, which has detrimental effects on children's educational attainment. At the same time, father absence is linked to better family economic resources, which is positively associated with children's educational attainment. When the father is absent, the mother may pay more attention to and show more love to children, which partially buffers the negative influence of father absence. Overall, results suggest that the loss of human capital at home resulting from father absence is the most important effect pathway linking father absence to educational attainment. Other positive influences of father absence, collectively, can only offset a small fraction (about a third) of this negative effect.

Finally, there are gender differences in effects and effect pathways. Greater family income in father-absent households benefits girls' educational attainment more than boys'. In contrast, there are no significant positive effects to offset the detrimental effects of father absence for boys. Finally, boys are more vulnerable than girls to father absence – father absence results in a larger reduction of total years of education for boys than for girls (0.517 years versus 0.338 years).

Due to data constraints, our research has some limitations. First, we only focus on father absence since only a small proportion of families have absent mother in our data. But our theoretical framework can be easily adapted to include mother absence or dual parent absence. Second, although in our analyses we mention the changes in family context associated with migrant father, what are measured in our dataset are essentially the differences between migrant and other families. Though GSCF is a longitudinal dataset, there is little change in families' migration status – in the second wave (2004) 98.35% of mothers stayed at home and only 8.83% of resident fathers in 2000 became migrants in 2004, which provides too few cases to do within-family comparison to trace the changes in family context due to parental absence. Thus, in this paper we have to employ a conventional technique like the one used in counterfactual analysis – taking non-migrant families as the control group to approximate the unmeasured pre-migration family context. Finally, despite the application of inverse probability weighting and the occasional use of words like "effect", we are not making causal arguments. Causation requires a more rigorous research design, which we will leave for future work. Rather, we are proposing a new framework which can provide a holistic review of how parental migration may associate with children's long-term educational outcome.

From a theoretical perspective, our analytical framework is useful in incorporating short-term and long-term perspectives and allowing for distinct effect pathways of parental absence via home-environment and child-development mechanisms. Furthermore, it allows for the connection and competition between different mechanisms underlying the association between parental absence and educational attainment, with each mechanism playing a controlling or mediating role for others, which helps to yield a more accurate estimate of each mechanism's effect. In addition, our framework enables the calculation and comparison of the relative importance of different effects/consequences, which facilitates a more comprehensive evaluation of the overall impact of parental absence and allows for assessment of group-specific heterogeneity of effects. Although our paper focuses on the case of China, this framework could be adapted to study the long-term impacts of parental migration on a serious of outcomes in different countries or regions.

Findings from this study are also relevant for informing policy and practice in China, to address the needs of left-behind children. While previous research shows both positive and negative effects of parental absence on children's educational and developmental outcomes, this paper finds that the loss in human capital due to father absence has the largest negative effect on children's educational attainment. This effect cannot be offset by other positive factors associated with father absence. Given the great importance of parental human capital for children's long-term educational outcomes, reducing policy barriers to schooling at destination cities so that children can remain together with parents is one obvious way to promote children's education and human capital accumulation. In the absence of such a policy, initiatives to provide more institutionalized academic support and advising to left-behind children are important, whether through boarding schools, if well managed (Xiao et al. 2010), or other full-service schools tailored to address the needs of children whose caregivers have limited experience with the educational system.

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Tables and Figures

Table 1 Descriptive Statistics

	Mean / Proportion	SD	Min	Max	N
Covariates in Propensity Score Model					
Child Demographics					
Age	11.093	1.159	8	16	2000
Gender (male=1, female=0)	0.536		0	1	2000
Family Structure					
Sibship size	2.247	0.749	0	5	2000
Child Health					
Chronic disease	0.023		0	1	2000
Child Education					
Retention	0.151		0	1	2000
Family Economic Capital					
Fixed assets and durable goods	6.686	11.144	0.057	153.760	2000
Family Cultural Capital					
Father's years of education	6.630	4.218	0	15	2000
Mother's years of education	3.701	4.033	0	14	2000
Family Social Capital					
Neighbor relationship in village	2.536	0.517	1	3	2000
Key Variables in Outcome Model					
Father Absence	0.196		0	1	2000
Economic Capital					
Family income per capita	1.645	2.948	0	81.320	2000
Human Capital					
Adults at home with reading ability	1.504	0.899	0	6	2000
Social Capital					
Parental warmth	38.748	5.364	18	54	1949
Doing things together	9.277	2.038	5	15	1981
Cultural Capital					
Number of books	27.991	21.099	0	160	1803
Non-Cognitive Skills					
Internalizing problems	39.975	8.140	18	72	1970
Externalizing problems	35.295	8.877	18	72	1976
Cognitive Skills					
Educational achievement	73.247	13.223	0	100	1951
Educational Attainment					
Years of education in 2015	11.387	3.537	0	19	1613
Auxiliary Variable					
Years of education in 2009	9.527	2.339	0	12	1833

Table 2 Maximum Likelihood Parameter Estimates in the Baseline Model of Predicting Educational Attainment by Father Absence

Parameter			Unstandardized Coefficient
Father Absence	→	Educational Attainment	-0.510* (0.228)
Age	→	Educational Attainment	-0.056 (0.081)
Male	→	Educational Attainment	0.501** (0.192)
Observations			2000

Note: Village-clustered robust standard errors in parentheses.
†< .1, *< .05, **< .01, ***< .001

Table 3 Data Balance Check

Covariate (As the Dependent Variable in a Bivariate Linear Regression or Logistic Regression)	Coefficient of Father Absence (As the Independent Variable in a Bivariate Linear Regression or Logistic Regression)	
	Before Weighting	After Weighting
Child Demographics		
Age	-0.004 (0.065)	-0.023 (0.080)
Gender (male=1, female=0)	0.082 (0.113)	0.083 (0.139)
Family Structure		
Sibship size	0.020 (0.042)	-0.005 (0.057)
Child Health		
Chronic disease	0.293 (0.352)	0.013 (0.402)
Child Education		
Retention	0.218 (0.151)	-0.187 (0.182)
Family Economic Capital		
Fixed assets and durable goods	-1.901** (0.627)	2.255 (2.696)
Family Cultural Capital		
Father's years of education	0.267 (0.238)	-0.173 (0.310)
Mother's years of education	-0.127 (0.227)	-0.161 (0.286)
Family Social Capital		
Neighbor relationship in village	-0.002 (0.029)	-0.018 (0.036)

Note: Standard errors in parentheses.
†< .1, *< .05, **< .01, ***< .001

Table 4 Significant Effect Pathways Linking Father Absence to Educational Attainment in the Full Model

Pathway from Father Absence to Educational Attainment							Effect Estimate	Subtotal
Father Absence	→Family income per capita				→	Educational Attainment	0.095† (0.053)	
	→Family income per capita	→Adults at home with reading ability			→		0.012 (0.009)	
	→Family income per capita	→Adults at home with reading ability	→Number of books		→		0.001 (0.001)	
	→Family income per capita	→Adults at home with reading ability	→Number of books	→Educational achievement	→		0.000 (0.000)	
	→Family income per capita	→Adults at home with reading ability	→Educational achievement		→		0.001 (0.001)	
	→Family income per capita	→Number of books			→		0.023 (0.018)	
	→Family income per capita	→Number of books	→Educational achievement		→		0.008 (0.005)	0.140* (0.069)
	→Adults at home with reading ability				→		-0.472*** (0.133)	
	→Adults at home with reading ability	→Number of books			→		-0.027 (0.019)	
	→Adults at home with reading ability	→Number of books	→Educational achievement		→		-0.009† (0.005)	
	→Adults at home with reading ability	→Educational achievement			→		-0.045† (0.025)	-0.552*** (0.137)
	→Parental warmth				→		0.048 (0.032)	0.048 (0.032)
Total								-0.364* (0.154)

Note: Village-clustered robust standard errors in parentheses. †< .1, *< .05, **< .01, ***< .001

Table 5 Significant Effect Pathways Linking Father Absence to Educational Attainment in Gender-Difference Models

Pathway from Father Absence to Educational Attainment						Effect Estimate		Subtotal	
						Male	Female	Male	Female
Father Absence	→Family income per capita				→ Educational Attainment	-	0.137 (0.106)		
Father Absence	→Family income per capita	→Adults at home with reading ability			→ Educational Attainment	-	0.026 (0.025)		
Father Absence	→Family income per capita	→Adults at home with reading ability	→Number of books		→ Educational Attainment	-	0.003 (0.003)		
Father Absence	→Family income per capita	→Adults at home with reading ability	→Number of books	→Educational achievement	→ Educational Attainment	-	0.001 (0.001)		
Father Absence	→Family income per capita	→Number of books			→ Educational Attainment	-	0.087 (0.061)		
Father Absence	→Family income per capita	→Number of books	→Educational achievement		→ Educational Attainment	-	0.017 (0.013)	-	0.270† (0.161)
Father Absence	→Adults at home with reading ability				→ Educational Attainment	-0.445* (0.195)	-0.528** (0.177)		
Father Absence	→Adults at home with reading ability	→Number of books			→ Educational Attainment	-	-0.067 (0.045)		
Father Absence	→Adults at home with reading ability	→Number of books	→Educational achievement		→ Educational Attainment	-	-0.013 (0.008)		
Father Absence	→Adults at home with reading ability	→Educational achievement			→ Educational Attainment	-0.072† (0.038)	-	-0.517** (0.198)	-0.608*** (0.178)
Total								-0.517** (0.198	-0.338 (0.213)

Note: Village-clustered robust standard errors in parentheses.
†< .1, *< .05, **< .01, ***< .00

Figure 1 Theoretical Framework

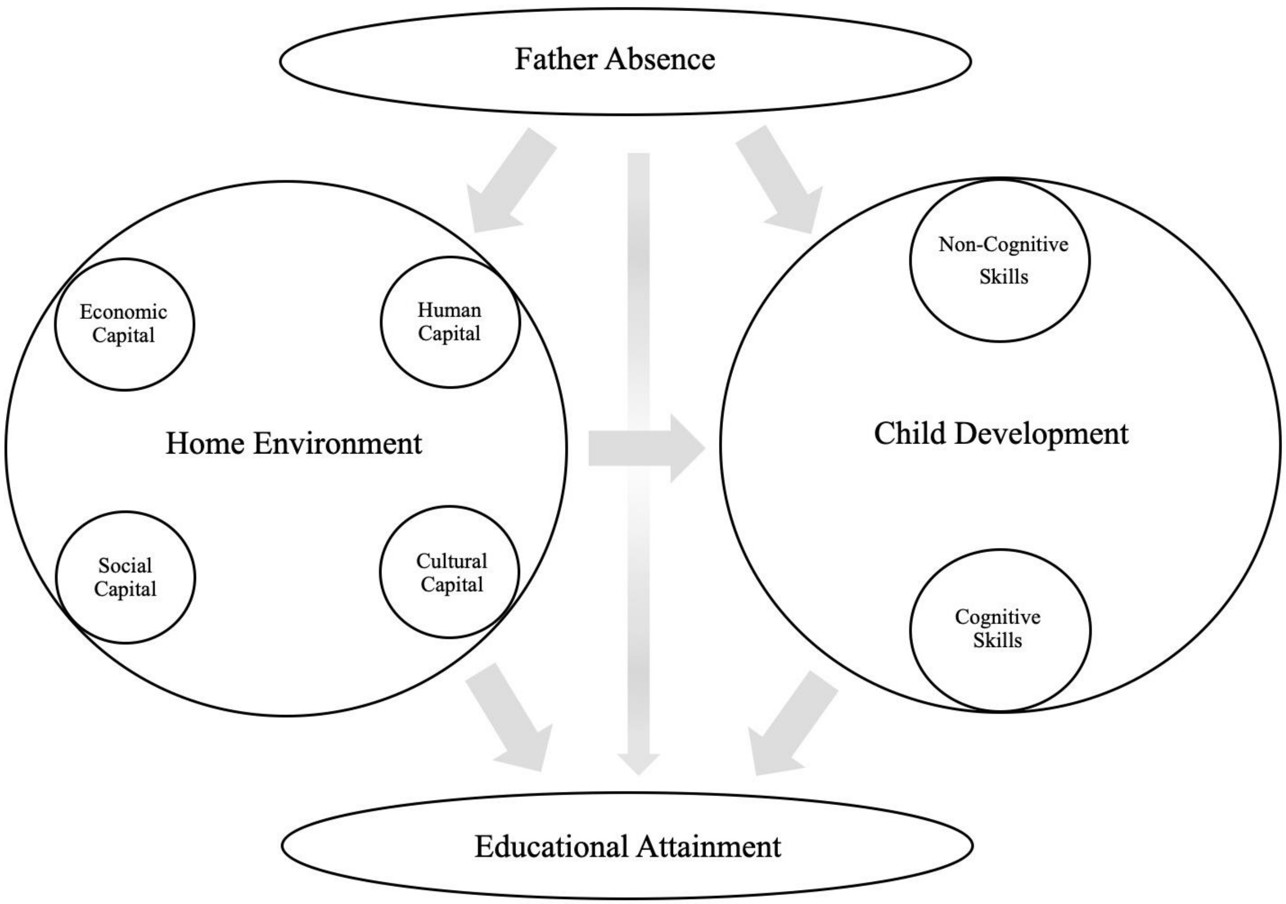
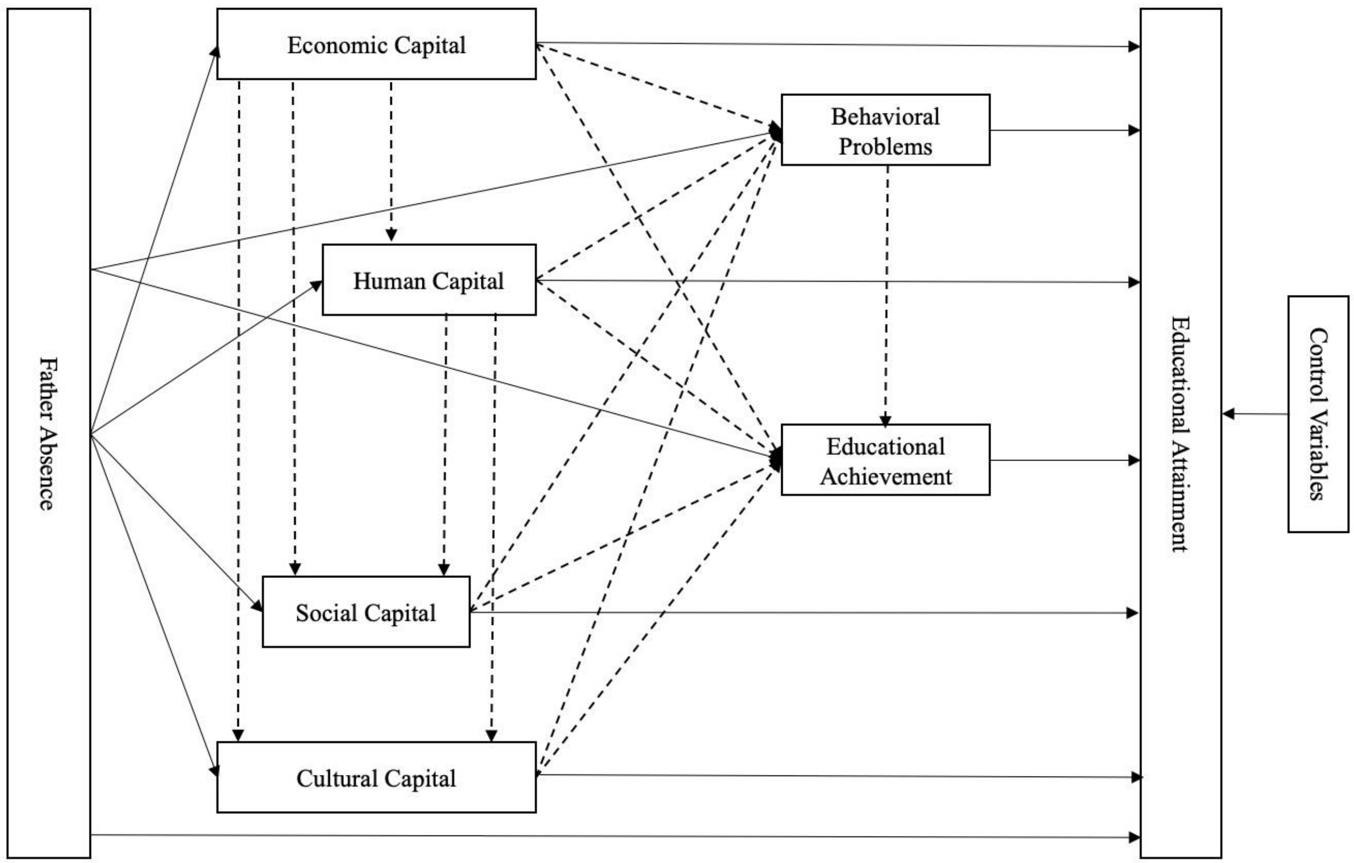


Figure 2 Diagram of the Full Model



Note: Dashed arrows represent the relationship between different home-environment and child-development mechanisms.

Appendix

Table A1 Weighted Maximum Likelihood Parameter Estimates in the Full Model of Linking Father Absence to Educational Attainment through Different Mechanisms

Parameter			Unstandardized Coefficient
Family income per capita			
	←	Father Absence	1.396† (0.715)
Adults at home with reading ability			
	←	Father Absence	-0.798*** (0.044)
	←	Family income per capita	0.015*** (0.004)
Parental warmth			
	←	Father Absence	0.725† (0.423)
	←	Family income per capita	0.055 (0.043)
	←	Adults at home with reading ability	0.170 (0.304)
Doing things together			
	←	Father Absence	0.214 (0.170)
	←	Family income per capita	0.048 (0.032)
	←	Adults at home with reading ability	0.470*** (0.113)
Number of books			
	←	Father Absence	-0.468 (1.497)
	←	Family income per capita	1.397*** (0.331)
	←	Adults at home with reading ability	2.891** (1.018)
Internalizing problems			
	←	Father Absence	0.048 (0.735)
	←	Family income per capita	-0.077 (0.084)
	←	Adults at home with reading ability	-0.248 (0.485)
	←	Parental warmth	-0.055 (0.135)
	←	Doing things together	-0.235 (0.237)

	←	Number of books	-0.022 (0.021)
Externalizing problems			
	←	Father Absence	0.881 (0.838)
	←	Family income per capita	-0.069 (0.060)
	←	Adults at home with reading ability	-0.570 (0.579)
	←	Parental warmth	-0.106 (0.134)
	←	Doing things together	-0.123 (0.243)
	←	Number of books	-0.027 (0.024)
Educational achievement			
	←	Father Absence	0.607 (0.897)
	←	Family income per capita	0.110 (0.141)
	←	Adults at home with reading ability	1.083† (0.563)
	←	Parental warmth	0.101 (0.133)
	←	Doing things together	0.366 (0.328)
	←	Number of books	0.078** (0.027)
	←	Internalizing problems	0.070 (0.130)
	←	Externalizing problems	-0.235* (0.109)
Educational Attainment			
	←	Father Absence	0.151 (0.243)
	←	Family income per capita	0.068* (0.029)
	←	Adults at home with reading ability	0.590*** (0.168)
	←	Parental warmth	0.067* (0.027)
	←	Doing things together	0.097 (0.074)
	←	Number of books	0.012† (0.007)

	←	Internalizing problems	0.003
			(0.032)
	←	Externalizing problems	-0.032
			(0.029)
	←	Educational achievement	0.052***
			(0.011)
	←	Age	-0.043
			(0.116)
	←	Gender (male=1, female=0)	0.675**
			(0.243)
Observations			2000

Note: Village-clustered robust standard errors in parentheses.
†< .1, *< .05, **< .01, ***< .001

Table A2 Weighted Maximum Likelihood Parameter Estimates in the Gender-Difference Model of Linking Father Absence to Educational Attainment through Different Mechanisms

Parameter			Unstandardized Coefficient	
			Male	Female
Family income per capita				
	←	Father Absence	0.543 (0.466)	2.456† (1.390)
Adults at home with reading ability				
	←	Father Absence	-0.862*** (0.061)	-0.722*** (0.068)
	←	Family income per capita	0.016 (0.004)	0.014* (0.006)
Parental warmth				
	←	Father Absence	0.657 (0.655)	0.672 (0.638)
	←	Family income per capita	0.131 (0.183)	0.049 (0.032)
	←	Adults at home with reading Ability	0.014 (0.457)	0.333 (0.360)
Doing things together				
	←	Father Absence	0.430* (0.197)	-0.075 (0.256)
	←	Family income per capita	0.183** (0.055)	0.033* (0.017)
	←	Adults at home with reading Ability	0.590*** (0.159)	0.340* (0.144)
Number of books				
	←	Father Absence	-2.191 (1.936)	1.604 (2.332)
	←	Family income per capita	0.933** (0.358)	1.505*** (0.428)
	←	Adults at home with reading Ability	2.076 (1.268)	3.927* (1.548)
Internalizing problems				
	←	Father Absence	-0.352 (0.904)	0.738 (1.098)
	←	Family income per capita	-0.324** (0.109)	0.033 (0.083)
	←	Adults at home with reading Ability	-0.709 (0.752)	0.410 (0.625)
	←	Parental warmth	-0.214 (0.164)	0.171 (0.181)
	←	Doing things together	-0.282 (0.308)	-0.139 (0.283)

	←	Number of books	0.018	-0.085*
			(0.023)	(0.033)
Externalizing problems				
	←	Father Absence	0.774	1.103
			(0.979)	(1.454)
	←	Family income per capita	-0.069	0.009
			(0.153)	(0.069)
	←	Adults at home with reading	-0.989	0.073
		ability	(0.802)	(0.861)
	←	Parental warmth	-0.289†	0.138
			(0.153)	(0.208)
	←	Doing things together	-0.210	-0.148
			(0.334)	(0.276)
	←	Number of books	0.017	-0.083*
			(0.026)	(0.037)
Educational achievement				
	←	Father Absence	1.674	-0.443
			(1.316)	(1.217)
	←	Family income per capita	-0.415	0.192†
			(0.323)	(0.114)
	←	Adults at home with reading	1.756*	0.261
		ability	(0.801)	(0.696)
	←	Parental warmth	0.006	0.328**
			(0.182)	(0.116)
	←	Doing things together	0.722*	0.131
			(0.368)	(0.422)
	←	Number of books	0.074*	0.064*
			(0.037)	(0.033)
	←	Internalizing problems	0.138	-0.137
			(0.160)	(0.154)
	←	Externalizing problems	-0.253†	-0.129
			(0.134)	(0.145)
Educational Attainment				
	←	Father Absence	0.190	0.056
			(0.331)	(0.311)
	←	Family income per capita	0.043	0.056†
			(0.054)	(0.034)
	←	Adults at home with reading	0.516*	0.732**
		Ability	(0.219)	(0.242)
	←	Parental warmth	0.098**	0.000
			(0.031)	(0.035)
	←	Doing things together	0.102	0.105
			(0.104)	(0.103)
	←	Number of books	0.003	0.024*
			(0.008)	(0.011)
	←	Internalizing problems	-0.025	0.064

		(0.036)	(0.049)
	← Externalizing problems	-0.002	-0.067
		(0.036)	(0.047)
	← Educational achievement	0.048***	0.071***
		(0.012)	(0.015)
	← Age	-0.067	0.092
		(0.162)	(0.148)
Observations		1072	928

Note: Village-clustered robust standard errors in parentheses.
†< .1, *< .05, **< .01, ***< .001