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Estimating the Causal Effect of Father Unemployment on the Propensity of Child School Dropout in Sudan

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Abstract

Unemployment and school dropout are two major economic problems in developing countries including Sudan. This paper estimates the causal effect of father unemployment on child school dropout using cross-section data from the National Baseline Household Survey in Sudan in 2009. We use a semi-parametric recursive bivariate probit model to control for the impact of the unobserved confounders and the endogeneity bias. Our results show that father unemployment increases child school dropout by 28 percentage points on average in the sample of all children. In rural areas, however, the impact reaches 42 percentage points. Sudan needs to make substantial reforms in the job-market regulations and structure and introduce policies related to job creation and protection. More importantly, Sudan needs to activate laws that make basic education compulsory, and to improve the education system structure.

تقدير التأثير السببي لبطالة الأب على احتمال سحب الأبناء من الدراسة في السودان

أبي الأمين

ملخص

البطالة والتسرب من المدارس مشكلتان اقتصاديتان رئيسيتان في البلدان النامية بما في ذلك السودان. هذه الورقة تقدر التأثير السببي لبطالة الأب على تسرب الأطفال من المدارس وذلك باستخدام بيانات مقطعية من المسح القومي للبيانات الأساسية للأسر في السودان في عام 2009. تستخدم نموذج احتمالي ثنائي المتغير شبه المعلمي للتحكم في تأثير عناصر الارتباك غير المشاهدة ومشكلة التحيز الأني. تظهر النتائج أن بطالة الأب تزيد من تسرب الأطفال من المدرسة بنسبة 28 نقطة مئوية في المتوسط. في المناطق الريفية يصل التأثير إلى زيادة احتمال تسرب الأطفال من الدراسة الى 42 نقطة مئوية. يحتاج السودان إلى إجراء إصلاحات جوهرية في لوائح سوق العمل وهيكله وإدخال سياسات تتعلق بخلق فرص العمل وحمايتها. والأهم من ذلك، يحتاج السودان إلى تفعيل القوانين التي تجعل التعليم الأساسي إلزاميًا وتحسين هيكل نظام التعليم.

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1. Introduction

School dropout is a common problem in developing countries including Sudan. For example, in sub-Saharan Africa Majgaard and Mingat (2012) show that the primary school intake is 96% for the children in the school entry age group but the completion rate is only 67%. They brought attention to the problem of data availability in the region to appropriately study the factors that lead to school dropout. Additionally, the report argues that school quality and high household education expenditures are some of the factors that lead to this stylised fact in sub-Saharan African countries. Inoue et al. (2015), on the other hand, argue that there are no "simple policy solutions exist" to the school dropout problem in Africa in general. However, studies that examine the impact of parents' or father labour market input on children's school dropout in the region are rare. In this research, we attempt to understand the causal effect of father unemployment on child school dropout at the microeconomic level in Sudan using cross-sectional data from the National Baseline Household Survey in 2009 (NBHS-2009). The research attempts to estimate the treatment effect of father unemployment on the propensity of child school dropout for the sample of the household that is covered in the survey.

Based on the World Bank, the macroeconomic indicators at the period of the NBHS-2009 survey show that the unemployment rate in Sudan increased from 13% in the year 2009 to 15.2% in 2010 and then to 17.4% in 2011. During the same period, the primary school enrolment rate dropped from 72.3% in 2009 to 71.1% in 2010 and then decreased to 69.5% in 2011. This indicates a strong causal effect between unemployment and human capital indicators in Sudan. It is crucial, however, to examine this causality at the microeconomic level to understand how the job market status of the family members affects the education decisions in the household. This information is important for economists, policymakers and educators because it helps on designing policies that can mitigate the negative impacts of unemployment and labour market shock on children and human capital building the economy.

However, estimating the causal effect of father unemployment on child school dropout is subject to an endogeneity problem. Both father unemployment and child school dropout are affected by unobserved common factors, unobserved confounders, that make them determined simultaneously in the model. On one hand, the general macroeconomic performance influences individuals' labour market inputs and education decisions, for example, the financial crisis of 2008–2009 (at the time of the NBHS-2009 survey period), corruption, bad policies and management and many other factors. On the other hand, personal and family-specific characteristics such as preferences, valuing of education, ability, education costs and opportunity cost and many other factors. The majority of these factors are not observed in our data. Accordingly, using a probit or logit model for estimating the impact makes the results subject to an endogeneity bias. The treatment effect will be biased toward zero, which means that the probit/logit model might indicate a very low or zero impact.

So, we use the recursive bivariate probit model to estimate the causal impact of father unemployment on the propensity that children dropout of school. The estimate is sensitive to the choice of the instrumental variables, where finding suitable variables to serve as IVs is a usually daunting process when using cross-sectional survey data. We find little support from the empirical literature in economics to provide us with insights about possible valid instrumental variables. So, we searched in our dataset for valid instruments and finally designed 5 sets and estimated the model using each set as presented in Section 5. This process can be considered also as a robustness check for our results in this research.

This research is motivated by the ambition to improve the living standard and the well-being of individuals and households in Sudan. It helps in understanding the problems that face human capital development and output production in the country since education is a basic component of building human capital and employment is the source of production. This paper reveals that Sudan in the period of the financial crisis in 2008-2009 has lost very high potential human capital that would have been crucial for development by now, due to the inadequate management of the country's labour market and education system during the crisis. Our paper contributes to the economic research literature in Sudan and Africa and discusses a crucial problem that is facing policymakers and economists. The practical and policy implications of this paper are that it helps in finding appropriate solutions for educational system problems that depend directly on the macroeconomic performance. This will help politicians in putting plans for sustainable economic development and for educational system practitioners to improve the efficiency of the education system.

The paper is organised as follows, Section 2 presents a literature review that covers some of the key studies that examine the impact of fathers' and parents' job loss and unemployment on children's academic achievement/progress and school drop-out. The section also presents the relevant studies that considered school dropout decisions in Africa and the region. Section 3 describes the model and the estimation technique that is used in this research, while Section 4 describes the data. Section 5 discusses the model estimates and explains the results. Finally, in Section 6 we demonstrate our conclusions and set the recommendations for the research.

2. Literature review

The job market in developed countries, and particularly in Africa, is distinguished in its structure, where it is characterised by the intensive use of low-skilled workers (Teal, 2000), the public sector crowds out the private sector which increases unemployment (Ranzani and Tuccio, 2017), and that the vast majority of self-employed individuals are females (Lain, 2019). Emmanuel (2022) adds that the job market and the human capital in Africa do not grow and develop with the development of technologies and the industrial revolution. In sub-Saharan African countries Fomba Kamga et al (2022) argue that political stability impact unemployment rates, particularly for the youth population.

The characteristics of the job market in Sudan is not substantially different than in other developing countries in Africa. However, the economic structure in Sudan is based on a large agricultural sector and a small industrial sector. Ahmed and Awadalbari (2014) using Okan's law, argue that there is a long-run relationship between real GDP and unemployment rate, which indicates that a high unemployment rate is associated with low GDP growth. However, Mustafa (2013) claims that the openness of the Sudan economy and oil revenues had negative impacts on unemployment rate, but ignores the consequences of the global financial crisis in 2008–2009. In a comprehensive review of the job market in Sudan, Nour (2011) shows that the political instability and the continuing civil wars are the two factors that specifically affect the economy and increased unemployment rate in the country. Additionally, Nour (2011) claims that the education vertical and horizontal mismatch is prevalent in the job market in Sudan, due to a shortage in the policies that motivate job creation and development and that organise the education system.

Lam et al. (2011), on the other hand, find that the youth in the households that experience negative shock in the job market is about 12 percentage points less likely to progress academically. Parents' unemployment causes poor health in children (Pieters and Rawlings, 2020) and has significant effects on later life welfare and satisfaction that extend to young adulthood (Nikolova and Nikolaev, 2021). Jürges et al. (2022) find that shock can make long-term negative impacts on families on the educational attainment of the children. Similar results are found by (Fischer et al., 2022; Ruiz-Valenzuela, 2021; Saad and Fallah, 2020).

Parent(s) job loss and father unemployment in particular impose many burdens on families, which can lead to negative consequences on the children's educational outcomes and future job-market inputs (Nikolova and Nikolaev, 2021). McKee-Ryan and Maitoza (2018) identify three negative consequences of parents' unemployment that directly affect children in the family, which are impact on mental health, child development and educational attainment. They argue that parents' unemployment increases learning difficulties for the children. This impact on child academic performance is studied further in economic (Mörk et al., 2019; Ruiz-Valenzuela, 2015). Ruiz-Valenzuela (2015) finds that father unemployment reduces average child grade by almost 13 percentage points. Stevens and Schaller (2011) find a negative effect on children's grades and grade retention. Di Maio and Nistico (2019), using data from Palestine, find that father unemployment increases child school dropout by 9 percentage points. TUTUNCULER (2022) finds that children of immigrant families are more likely to drop out of school.

As a natural outcome of compulsory education laws, studies in developed and western countries mostly focus on the impact of parental job loss and father unemployment on the school progress and achievement of the children at the basic education level. Many papers, however, focus on the impact on the decision to continue studying after finishing basic education (Hajdu et al., 2019), and post-secondary and college enrolment decision (Hilger, 2016). Pan and Ost (2014) find that parental job loss when the children were between ages 15 and age 17 decreases the propensity of enrolment in college by about 10 percentage points. Oreopoulos et al. (2008) use Canadian data and find that children whose fathers had employment shocks have 9% less annual earnings in adulthood compared with those whose fathers did not experience similar shocks. In contrast, in developing countries interest is directed more to examining the impact of parents' or fathers' unemployment on school dropout even before completing the basic education. This kind of education interruption has more severe consequences, not only on children's future job market inputs and level of welfare, but also on the country's economic development (Gyimah-Brempong, 2011).

In Africa, Chinyoka (2014) examines the causes of school dropout in Zimbabwe, without considering parent(s) job loss, and finds that poverty and broken family, as well as children's lack of interest in education, are the main factors driving school drop-out. Similarly, Woldehanna and Hagos (2015) argue that primary school dropout in Ethiopia is affected by shocks in the household but without considering father or parent(s) unemployment in the model. Bedi et al. (2004) examine factors such as school fees, curriculum, school availability, and the expected benefits of education on primary school enrolment. Their results show that at the lowest expenditure quantile a 100 percentage points increase in school fees decreases the enrolment rate by about 12 percentage points. Generally, Iscan et al. (2015) find that school fees in sub-Saharan Africa have reduced primary school enrolment, but Ali and Soharwardi (2022) argue that the impact can extend further and drive children to child labour. In India, Hoque et al. (2022) find a significant effect of removing school fees on the propensity of child school drop-out.

Glick et al. (2016) examine the role of household shocks on children's school dropout in Madagascar and find a significant effect on health, asset shock or death of a family member. Their results suggest that labour market 'rigidities' do not have an influence on child school enrolment or dropout, where the father job loss variable is insignificant in their model. Krutikova et al. (2010), using a sample from rural Tanzania, show that household income shocks have permanent negative outcomes on education for children in the age group 7-15 years old. The impact of father and parents' education on school dropout of children is discussed by Mani et al. (2009) who show that father schooling impacts child school performance in Ethiopia.

Dostie and Jayaraman (2006) find that school dropout decreases with higher parental education levels as well as wealth. Household characteristics and social backgrounds such as poor parents' education, number of children and family members increase the propensity of children to drop out of school (Farah and Upadhyay, 2017). Moeeni (2022) finds intergenerational effects of economic sanctions, where families reduce education spending due to the increase in living costs. Sudan has been under economic sanctions for several years and this factor likely impacted school dropout decisions from many families. In Sudan, school dropout is examined by Fincham (2019), which concludes that most of the significant factors affecting dropout are originated from home and are community. However, this study focuses on girls' school dropout in the Red Sea state only.

The recursive bivariate probit model is commonly used to estimate factors affecting dropout decisions in the education system, for example, Di Pietro (2004) in the case of Italy and Guimarães et al. (2010) in the case of Brazil. Kuépié et al. (2015) applied the model to estimate the factor that affects school dropout in Sub-Saharan African countries and find a significant impact on poverty, gender discrimination and weak performance at school. On the other hand, the semi-parametric recursive bivariate probit model of Marra and Radice (2011) is used by Elamin et al. (2019) to study the impact of private tutoring on parents' work decisions. Attempts to use the semi-parametric recursive bivariate probit model to estimate the causal effect of unemployment on human capital variables in Sudan or Africa have not appeared to us.

3. Econometric technique

Our interest is to estimate the causal effect of a dummy variable d, the father unemployment indicator, on child school dropout which is represented by a dummy variable s. Both d and s are defined as dichotomous variables for unobserved continuous latent variables d^* and s^*. Due to the impact of common unobserved confounders s and d are determined simultaneously, which causes an endogeneity problem in the model. Then the estimated causal effect of d on s will be inconsistent if the univariate probit model is used. Fortunately, the recursive bivariate probit model provides a solution that allows for estimating the causal effect consistently, by allowing for controlling for the observed confounders and accounting for the effect of the unobserved confounders simultaneously. The recursive bivariate probit model is constructed from two equations that take the following form:

$$s_i = I\left(\alpha d_i + \mathbf{w}_{i,1}'\boldsymbol{\gamma}_1 + \mathbf{x}_{i,1}'\boldsymbol{\beta}_1 + \varepsilon_{i,1} > 0\right), \quad (1)$$

$$d_i = I\left(\mathbf{w}_{i,2}'\boldsymbol{\gamma}_2 + \mathbf{x}_{i,2}'\boldsymbol{\beta}_2 + \varepsilon_{i,2} > 0\right), \quad (2)$$

where $I(\cdot)$ is an indicator function that equals 1 if the argument in the parentheses is true and zero otherwise. Clearly the dichotomous variables are $s_i^* = \alpha d_i + \mathbf{w}_{i,1}'\boldsymbol{\gamma}_1 + \mathbf{x}_{i,1}'\boldsymbol{\beta}_1 + \varepsilon_{i,1}$ and $d_i^* = \mathbf{w}_{i,2}'\boldsymbol{\gamma}_2 + \mathbf{x}_{i,2}'\boldsymbol{\beta}_2 + \varepsilon_{i,2}$. The vector $\mathbf{w}_{i,1}$ includes the dummy variables that represent the categorical exogenous variables in the first equation, while $\mathbf{w}_{i,2}$ in Eq 2 is the vector of the dummy variables in the second equation. The vectors $\mathbf{x}_{i,1}$ and $\mathbf{x}_{i,2}$ contain the continuous exogenous variables in Eq 1 and Eq 2, respectively. The coefficient vectors are defined as $\boldsymbol{\gamma}_j$ and $\boldsymbol{\beta}_j$, where $j = 1,2$. The vectors $\mathbf{w}_{i,2}$ and $\mathbf{x}_{i,2}$ include the instrumental variable in addition to the variables appearing in $\mathbf{w}_{i,1}$ and $\mathbf{x}_{i,1}$.

The error terms in the equations are assumed to follow a bivariate normal distribution with mean $\mathbf{0}$, unite variance and correlation between the errors equals ρ, i.e.

$$\begin{pmatrix} \varepsilon_{i,1} \\ \varepsilon_{i,2} \end{pmatrix} \sim N(\mathbf{0}, \boldsymbol{\Sigma}), \quad (3)$$

where $\boldsymbol{\Sigma}$ is a 2×2 the covariance (correlation) matrix with main diagonal equals 1 and off-diagonal value ρ.

The model is estimated using the maximum likelihood method that maximizes the function:

$$Log(L) = \sum_{i=1}^{n} \Phi_2\left(t_{i,1}, t_{i,2}, \rho\right) \quad (4)$$

where $t_{i,1}$ and $t_{i,2}$ are linear functions on the variables and the coefficients as defined by Greene (2012). Φ_2 is a bivariate standard normal cumulative distribution function. The recursive bivariate probit model identifies the four possible outcomes of s and d variables, which are $(s_i = 0, d_i = 0)$, $(s_i = 1, d_i = 0)$, $(s_i = 0, d_i = 1)$ and $(s_i = 1, d_i = 1)$, to estimate the joint probability of the endogenous variables conditional on the exogenous variables. The marginal probability of d_i is given directly using univariate normal cumulative distribution function, see Greene (2012). The log-likelihood function can be expressed as:

$$l(\boldsymbol{\delta}) = \sum_{i=1}^{n} \{ s_i d_i p_{11,i} + s_i(1-d_i)p_{10,i} + (1-s_i)d_i p_{01,i} + (1-s_i)(1-d_i)p_{00,i} \}, \tag{5}$$

which is maximized with respect to $\boldsymbol{\delta}' = (\alpha, \boldsymbol{\gamma}_1{}', \boldsymbol{\gamma}_2{}', \boldsymbol{\beta}_1{}', \boldsymbol{\beta}_2{}', \rho)$. $p_{m_1 m_{2,i}}$, where m_1 and m_2 are either 0 or 1, are the probabilities of the possible four outcome that are defined above. The coefficient of primary interest in the model is α in Eq 1, which captures the treatment effect. The correlation coefficient between the error terms, $\hat{\rho}$, indicates the strength of the endogeneity problem in the model. The closer the absolute value of $\hat{\rho}$ to 1 the stronger the endogeneity problem in the model, which makes the estimator of α inconsistent if the effect of the unobserved confounder is ignored.

Our interest is to consistently estimate the parameter α, the correlation coefficient ρ and the coefficient vectors $\boldsymbol{\gamma}_j$ and $\boldsymbol{\beta}_j$, denoted as $\hat{\alpha}$, the correlation coefficient $\hat{\rho}$ and the coefficient vectors $\hat{\boldsymbol{\gamma}}_j$ and $\widehat{\boldsymbol{\beta}}_j$. Then estimate average treatment effect, $\hat{\delta}$, using the cumulative standard normal distribution function , $\boldsymbol{\Phi}$, as follows:

$$\hat{\delta} = \boldsymbol{\Phi}\{\hat{\alpha} + \mathbf{w}_{i,1}{}'\hat{\boldsymbol{\gamma}}_1 + \mathbf{x}_{i,1}{}'\widehat{\boldsymbol{\beta}}_1\} - \boldsymbol{\Phi}\{\mathbf{w}_{i,1}{}'\hat{\boldsymbol{\gamma}}_1 + \mathbf{x}_{i,1}{}'\widehat{\boldsymbol{\beta}}_1\}. \tag{6}$$

The delta method is used to estimate the standard error of the ATE from the recursive bivariate probit model and then the 95% confidence interval is constructed.

Chib et al. (2009) show that inappropriate detection of non-linearities in the recursive bivariate probit model impacts the quality of the results and accordingly the ATE estimate. One major outcome is that the joint density of the error terms can appear as non-Gaussian even when the data generating process is Gaussian, which incorporate risks of having misspecification problem in the model. To overcome this problem Marra and Radice (2011) developed a semi-parametric specification for the recursive bivariate probit model by using non-parametric functions for smoothing the continuous covariates as follows

$$s_i = I\left(\alpha d_i + \mathbf{w}_{i,1}{}'\boldsymbol{\gamma}_1 + \sum_{k_1=1}^{K_1} f_{k_1}(x_{i,1,k_1}) + \varepsilon_{i,1} > 0\right), \tag{7}$$

$$d_i = I\left(\mathbf{w}_{i,2}{}'\boldsymbol{\gamma}_2 + \sum_{k_2=1}^{K_2} f_{k_2}\left(x_{i,2,x_{k_2}}\right) + \varepsilon_{i,2} > 0\right). \tag{8}$$

The functions f_{k_1} and f_{k_2} are unknown smooth functions but can be approximated using the penalized regression splines. K_1 and K_2 are the number of continuous independent variables in Eq 7 and Eq 8, receptively.

The semi-parametric specification flexibly controls for the effect of the continuous independent variables in the model and it does not require using forms such as quadratic or cubic. However, the estimation procedure includes a trading-off between fit and smooth and uses penalties during the model fit. The optimum coefficients and smoothing parameters are achieved by maximising the so-called penalised log-likelihood function that is given as:

$$l(\boldsymbol{\delta})_p = l(\boldsymbol{\delta}) - \frac{1}{2}\boldsymbol{\delta}'\mathbb{S}_\lambda \mathbf{S}, \tag{9}$$

where $\mathbb{S}_\lambda = \sum_{v=1}^{2}\sum_{k_v=1}^{K_v}\mathbb{S}_{K_v}$ and that $\mathbb{S}_{K_v}$ are square positive semi-definite matrices that are known and measure the roughness of the smooth terms in the model.

The average treatment effect is directly estimated using the formula:

$$\hat{\delta} = \boldsymbol{\Phi}\left\{\hat{\alpha} + \mathbf{w}_{i,1}{}'\hat{\boldsymbol{\gamma}}_1 + \sum_{k_1=1}^{K_1}\hat{f}_{k_1}(x_{i,1,k_1})\right\} - \boldsymbol{\Phi}\left\{\mathbf{w}_{i,1}{}'\hat{\boldsymbol{\gamma}}_1 + \sum_{k_1=1}^{K_1}\hat{f}_{k_1}(x_{i,1,k_1})\right\}. \tag{10}$$

In contrast to the fully parametric estimator, the 95% confidence intervals for the semi-parametric estimator are constructed using Bayesian simulation from the posterior distribution of coefficients and the smoothing parameters. In this research, we compare the estimates of the average treatment effect from both techniques as presented below.

Testing for the absence of endogeneity, i.e. testing the homogeneity of the treatment, is equivalent to testing the null hypothesis that the correlation coefficient between the error terms in the equations equals zero. So, the null hypothesis $H_0: \rho = 0$ could be tested against the alternative hypothesis $H_0: \rho \neq 0$ using the Wald test by computing the test statistic as follows:

$$\frac{\widehat{\rho^*}^2}{Var(\widehat{\rho^*})}, \tag{11}$$

which is under the null hypothesis converges to a chi-square distribution with 1 degree of freedom and that $\rho^* = \frac{1}{2}log[(1+\rho)/(1-\rho)]$.

4. Data

The National Baseline Household Survey (NBHS) was conducted by the Central Bureau of Statistics in the Republic of Sudan in 2009 and covers many educational, employment, health and welfare measures. The data is obtained from the Central Bureau of Statistics website in 2014. The number of households in the survey is 7913 with total household members of 48845 individuals. The questions about school absence/dropout targeted the children in the age group 6-15 in the sample. The school dropout dummy variable takes a value of one if at least one reason for not attending school is specified. We include only the children living with their parents with the father being the head of the household. Accordingly, children who are living in extended families, where the head of the household could be a grandfather, an uncle, a step-grandfather or any other person in the family; children who are living with a mother head of household; and children who are living with relatives, are all excluded from the analysis. Additionally, we have dropped all the cases with missing values. Thus, the final sample size contains only 10650 children.

The set of the independent variables includes child age, male dummy, number of household members, number of children in school age 6-16 in the household, the share of per-capita education expenses from the total per-capita expenditures, the share of house-related expenses, the log per-capita total expenditures, a dummy that equals 1 if the mother lives in the same household, an urban area dummy variable, and state dummies variables. In the fully parametric recursive bivariate probit model, we use the quadratic form of child age.

Table 1 presents the summary statistics for the child's school dropout indicator, the father's unemployment indicator and the covariates that are used in the model. The dropout rate is about 30% in the sample of all children, but in the rural areas, it is more than double the rate in the urban areas, where it is 36% compared with 14.8% in the urban. Similarly, the father unemployment rate is 18.2% in the sample of all children, 13.5% in the urban and increases to 20% in the rural. The sample means of the covariates are balanced in the treatment and control groups that are determined by the father's unemployment status. This ensures that the overlap of the treatment condition is satisfied in the model, which reduces the bias in the final treatment effect estimate.

The summary statistics in Table A2 show that the father education level is not stated for about 42% of the children in the sample, which is equivalent to 4480 cases in our sample. Table 1 presents the t-test for mean equality in the treatment and control groups, only two variables are weakly balanced, the number of households and log household total expenditures. Additionally, the distribution of father education level is not balanced in the father unemployment status groups, except the primary school/Kalwa[(1)] and the secondary school dummy variables, which are balanced in the urban and rural sub-samples also. This makes using the dummies for all the categories of father education level in covariate set in the model unsuccessful. As being unbalanced variables in the treatment and control group this will make weak overlap at certain ranges of the covariate set, which affects the ATE estimate. Thus, we include only the balanced dummies which are the father primary school/Kalwa dummy and the secondary school education dummy.

Table (1): Summary statistics

Variable^{b}	mean	sd	Father job market status					
			Employed		Unemployed		$H_0: \bar{x}_{j,e} - \bar{x}_{j,u} = 0^{a}$	
			mean	sd	mean	sd	t −value	p.value
Sample of all children								
dropout	0.301	0.459	0.293	0.455	0.336	0.473		
F. unemployed	0.182	0.386						
Age	10.20	2.847	10.18	2.848	10.31	2.839	-1.90	0.056
Male	0.526	0.499	0.528	0.499	0.515	0.500	1.10	0.276
HH members	8.210	2.532	8.167	2.512	8.405	2.613	-3.75	0.000
No. children	3.303	1.414	3.310	1.420	3.270	1.384	1.15	0.256
Sh. education	2.039	3.328	2.030	3.343	2.075	3.262	-0.55	0.592
Sh. house	5.061	3.418	5.034	3.349	5.183	3.709	-1.75	0.085
log exp.	4.631	0.598	4.657	0.593	4.514	0.609	9.55	0.000
Mother in HH	0.970	0.170	0.971	0.167	0.965	0.183	1.40	0.156
F. primary	0.329	0.470	0.331	0.471	0.321	0.467	0.85	0.406
F. secondary	0.101	0.302	0.102	0.303	0.0992	0.299	0.35	0.725
Urban	0.289	0.453	0.305	0.460	0.214	0.411	8.00	0.000
n	10,650		8,715		1,935			
Urban sub-sample								
dropout	0.148	0.355	0.149	0.356	0.145	0.352		
F. unemployed	0.135	0.342						
Age	10.34	2.829	10.31	2.831	10.54	2.805	-1.60	0.110
Male	0.514	0.500	0.515	0.500	0.511	0.500	1.30	0.195
HH members	7.964	2.357	7.901	2.222	8.369	3.057	-1.75	0.079
No. children	3.113	1.318	3.119	1.299	3.072	1.438	1.70	0.089
Sh. education	2.887	3.985	2.858	4.059	3.068	3.474	-1.60	0.105
Sh. house	5.100	3.723	5.052	3.572	5.407	4.567	-1.00	0.316
$log(exp)$	4.945	0.554	4.950	0.554	4.913	0.556	7.60	0.000
Mother in HH	0.976	0.154	0.977	0.151	0.969	0.174	0.90	0.356

[(1)] Kalwa is a traditional religious school that teaches Quran and basic Arabic language and mathematics.

Variable^{b}	mean	sd	Father job market status					
			Employed		Unemployed		$H_0: \bar{x}_{j,e} - \bar{x}_{j,u} = 0^{a}$	
			mean	sd	mean	sd	t −value	p.value
F. primary	0.372	0.484	0.375	0.484	0.357	0.480	0.01	0.986
F. secondary	0.187	0.390	0.184	0.387	0.212	0.409	-0.35	0.740
n	3,074		2,659		415			
Rural sub-sample								
drop-out	0.363	0.481	0.356	0.479	0.389	0.488		
F. unemployed	0.201	0.401						
Age	10.15	2.852	10.12	2.854	10.25	2.846	-1.60	0.111
Male	0.531	0.499	0.534	0.499	0.516	0.500	0.15	0.879
HH members	8.310	2.593	8.284	2.621	8.414	2.479	-3.75	0.000
No. children	3.380	1.444	3.394	1.463	3.324	1.364	0.65	0.500
Sh. education	1.694	2.953	1.667	2.901	1.804	3.149	-1.00	0.320
Sh. house	5.046	3.286	5.027	3.247	5.121	3.437	-1.80	0.070
$log(exp)$	4.503	0.567	4.528	0.562	4.405	0.576	1.25	0.204
Mother in HH	0.968	0.176	0.969	0.173	0.964	0.185	1.00	0.326
F. primary	0.312	0.463	0.312	0.463	0.312	0.463	0.70	0.473
F. secondary	0.067	0.249	0.0661	0.248	0.0684	0.253	-1.40	0.166
n	7,576		6,056		1,520			

[a] t-test for the equality of means in the father unemployment status groups, assuming unequal variance to account for suspected heteroskedasticity.
[b]The description of the variables is provided in Table A1 in Appendix A.

5. Results

We estimate the recursive bivariate probit model using 5 sets of instrumental variables which have been chosen after studying the correlations of all the variables that can serve as IVs in the survey dataset. The valid IVs should be correlated with the endogenous variable, d_i , but not correlated with the outcome variable, s_i, and the error term,$\varepsilon_{i,1}$. The first set, denoted as IV1, includes the variables: father's age; pre-capita household expenditure on sports equipment, camping and outdoor recreation; a dummy of whether the household was subject to a robbery, burglary or assault in the past 5 years. The second set, IV2 includes in addition to the variables in IV1; consumption of cooked food from vendors; and the number of mosquito nets owned by the household a quantitative variable equals the father's consumption of tobacco and a dummy for whether the father is older than the working age, i.e. father's age ≥ 65. IV3 includes all the variables in the set IV2 in addition to two new variables which are, the total number of rooms and dummies of tenure status of household dwelling. Set IV4 includes in addition to the variables in set IV3 a dummy variable for the group of children with a father education level not stated. Set IV5, adds a quantitative variable that equals the total number of rooms, then in the last set, we add a dummy variable that equals 1 if the family owns the dwelling. The last three sets attempt to utilize some of the information about the father education level variable in the model in addition to the two balanced father education dummies that are used as covariates.

Table 2 presents the estimated coefficients for the father unemployment dummy using the linear probability model (LPM). These estimates are consistent but the traditional problem of LPM is that the prediction may not be in the $[0,1]$ range. The OLS estimate indicates that father unemployment increases child school dropout by 2 percentage points only and that the effect is significant at a 5% level of significance. The two-stage least squares estimates suggest that the effect is substantially higher and ranges between 22-40 percentage points. The endogeneity problem is present in the model, based on j test statistics, which also indicate that the exclusion restriction condition of the instrument variable is satisfied. Additionally, the estimates seem to be highly sensitive to the choice of the instrumental variables set. The LPM can capture the effect in the sample of all children only, in the urban and rural subsamples the coefficient of father unemployment is insignificant.

The estimates of the average treatment effect for the father unemployment on child dropout using the fully parametric bivariate probit model are presented in Table 3. The first column reports the ATE of father unemployment that is estimated by the probit model, under the exogeneity assumption of the treatment and the outcome. However, the test of exogeneity indicates that child school dropout and father unemployment are both affected by common unobserved confounders in the model, and that the father unemployment dummy is endogenous. In contrast to the estimates from the two-stage least squares model, the bivariate probit model estimates significant coefficients in the sub-samples. However, in the rural sub-sample, the ATE becomes highly significant when the IV sets that control for the missing information about the father education level are used. All the models in the table produced a negative estimate for the correlation coefficient between the error terms, ρ.

The results show that father unemployment increases the propensity of child dropout of school by 33.3 percentage points. In the urban, the effect is only 21 percentage points. The marginal effects coefficients for all the independent variables in the model are reported in Table 3 and in Appendix A in the Tables A3 to A5. The estimated marginal effect coefficients for the other independent variables in the model are not sensitive to the choice of the instrumental variables as much as the estimated coefficient for the father unemployment dummy. Additionally, values of the estimated marginal effects are not largely different from those estimated by the univariate probit model under the exogeneity assumption except for the endogenous treatment dummy. This indicates that other covariates are exogenous and that using the recursive bivariate probit model was appropriate in this setting.

Table (2): Estimated coefficients of ordinary least squares and two-stage least squares model[a,d]

	OLS	**Two-stage least squares**[b]				
		IV1	**IV2**	**IV3**	**IV4**	**IV5**
All children[c]						
F. unemployed	0.030***	0.267***	0.348***	0.272***	0.275***	0.304***
	(0.011)	(0.094)	(0.092)	(0.091)	(0.091)	(0.090)
R-squared	0.234	0.197	0.167	0.195	0.194	0.184
RSS	1715	1799	1866	1803	1805	1827
F	144.0	135.6	130.1	135.4	135.2	133.3
***j* stat.**		25.47	54.40	188.4	195.5	198.8
p-value *j*		0.000	0.000	0.000	0.000	0.000
***j* stat. df**		2	6	7	8	9
Urban sub-sample						
F. unemployed	0.015	0.037	0.146	0.025	0.033	0.063
	(0.017)	(0.133)	(0.126)	(0.122)	(0.122)	(0.121)
R-squared	0.202	0.202	0.187	0.202	0.202	0.200
RSS	309.8	309.9	315.5	309.8	309.9	310.6
F	21.54	21.51	21.20	21.52	21.51	21.46
***j* stat.**		12.85	50.55	78.70	81.45	87.30
p-value *j*		0.002	0.000	0.000	0.000	0.000
***j* stat. df**		2	6	7	8	9
Urban sub-sample						
F. unemployed	0.028**	0.155	0.217**	0.200*	0.195*	0.231**
	(0.013)	(0.107)	(0.105)	(0.104)	(0.104)	(0.104)
R-squared	0.216	0.205	0.192	0.196	0.197	0.188

	OLS	Two-stage least squares[b]				
		IV1	IV2	IV3	IV4	IV5
RSS	1374	1392	1414	1408	1406	1421
F	100.1	98.54	96.77	97.31	97.45	96.18
j stat.		32.48	41.91	139.6	145.0	149.4
p-value j		0.000	0.000	0.000	0.000	0.000
j stat. df		2	6	7	8	9

a. Coefficients of other independent variables in the model are not presented for brevity but are available from the author on request. Robust standard errors in brackets.

b. The instrumental variables are described in Section 5.

c. Number of observations: sample of all children = 10650, urban sub-sample 3074, rural sub-sample 7576

d. $*** p < 0.01, ** p < 0.05, * p < 0.1$.

The semi-parametric bivariate probit model estimates are reported in Table 4. The confidence intervals of the estimated ATE and the correlation coefficient of the error terms are constructed using 1000 Bayesian samples drawn from the posterior distribution of the parameters. In contrast to the fully parametric model estimates in Table 3, all the estimates of the semi-parametric model are significant at a 5% level of significance. The 95% confidence interval is all in the positive domain for the ATE and in the negative domain for the correlation coefficient and is narrower than those constructed from the fully parametric bivariate probit model in Table 3.

However, similarly to the fully parametric models, the strongest rejection for the exogeneity assumption appeared when set IV5 is used, combined with the highest estimate for the correlation between the error terms. Semi-parametric model estimates are less disparate when different IV sets are attempted, which indicates that the model utilises the observed heterogeneity in the independent variables more efficiently than the fully parametric bivariate model. Relaxing the functional form of the continuous variables and using the smoothing techniques has improved the quality of the results. In the sample of all children, the estimated effect is about 28 pp and increases to 42 pp in rural areas. This is slightly lower than the estimates from the fully parametric model but the estimates of ρ suggest a stronger correlation between the error terms. The unobserved confounders that affect both father unemployment and child school dropout seem to be different in the urban areas than in the rural areas. The value of the estimated correlation coefficient between the error terms is higher in absolute value in the rural areas subsample.

Table (3): Estimated ATE Using the Fully Parametric Bivariate Probit Model[a,b,e]

	Probit	**Fully parametric bivariate probit model[c]**				
		IV1	**IV2**	**IV3**	**IV4**	**IV5**
All children[d]						
$\hat{\delta}$	0.024** (0.010)	0.247*** (0.061)	0.268*** (0.054)	0.290*** (0.055)	0.293*** (0.054)	0.301*** (0.050)
95% IC $\hat{\delta}$	{0.004, 0.044}	{0.128, 0.367}	{0.163, 0.374}	{0.181, 0.399}	{0.187, 0.400}	{0.203, 0.399}
$\hat{\rho}$		-0.436	-0.474	-0.514	-0.520	-0.535
95% CI $\hat{\rho}$		{-0.625, -0.198}	{-0.641, -0.265}	{-0.680, -0.297}	{-0.683, -0.307}	{-0.685, -0.341}
Wald		11.79	17.20	18.09	19.11	23.39
P-value Wald		0.001	0.000	0.000	0.000	0.000
Urban sub-sample[d]						
$\hat{\delta}$	0.015 (0.016)	0.199** (0.088)	0.218*** (0.068)	0.211*** (0.080)	0.210*** (0.081)	0.217*** (0.073)
95% IC $\hat{\delta}$	{-0.017, 0.477}	{0.026, 0.372}	{0.084, 0.351}	{0.054, 0.367}	{0.050, 0.370}	{0.074, 0.360}
$\hat{\rho}$		-0.534	-0.585	-0.567	-0.565	-0.585
95% CI $\hat{\rho}$		{-0.836, 0.016}	{-0.823, -0.174}	{-0.837, -0.074}	{-0.840, -0.060}	{-0.834, -0.136}
Wald		3.64	7.05	4.90	4.67	6.08
P-value Wald		0.056	0.008	0.027	0.031	0.014
Rural sub-sample[d]						
$\hat{\delta}$	0.022* (0.012)	0.220* (0.124)	0.238** (0.105)	0.299*** (0.073)	0.304*** (0.069)	0.307*** (0.065)
95% IC $\hat{\delta}$	{-0.002, 0.046}	{-0.023, 0.463}	{0.033, 0.444}	{0.156, 0.441}	{0.168, 0.441}	{0.179, 0.434}
$\hat{\rho}$		-0.388	-0.426	-0.552	-0.564	-0.568
95% CI $\hat{\rho}$		{-0.754, 0.162}	{-0.745, 0.052}	{-0.780, -0.194}	{-0.783, -0.221}	{-0.776, -0.250}
Wald		1.96	3.10	8.23	9.14	10.53
P-value Wald		0.161	0.079	0.004	0.003	0.001

a. Delta method standard errors are in the brackets. 95% confidence intervals of the estimated ATE and ρ in curly brackets.

b. Marginal effects of the complete set of independent variables in the model are presented in Tables *5* to *7* in Appendix *7*.

The instrumental variables are described in Section 5.

c. Number of observations: sample of all children = 10650, urban sub-sample 3074, rural sub-sample 7576

d. *** p<0.01, ** p<0.05, * p<0.1.

Table (4): Estimated ATE Using the Semiparametric Bivariate Probit Model[a,b,e]

	IV1	IV2	IV3	IV4	IV5
All children[c]					
$\hat{\delta}$	0.268	0.270	0.277	0.279	0.284
95% IC $\hat{\delta}$	{0.192, 0.347}	{0.197, 0.346}	{0.206, 0.351}	{0.211, 0.351}	{0.220, 0.350}
$\hat{\rho}$	-0.522	-0.525	-0.539	-0.542	-0.552
95% CI $\hat{\rho}$	{-0.640, -0.382}	{-0.638, -0.403}	{-0.639, -0.395}	{-0.653, -0.427}	{-0.654, -0.390}
Wald	40.21	42.20	45.29	46.27	50.68
P-value Wald	0.000	0.000	0.000	0.000	0.000
Urban sub-sample[c]					
$\hat{\delta}$	0.284	0.295	0.287	0.283	0.289
95% IC $\hat{\delta}$	{0.143, 0.441}	{0.159, 0.441}	{0.144, 0.437}	{0.143, 0.445}	{0.151, 0.426}
$\hat{\rho}$	-0.598	-0.622	-0.608	-0.601	-0.613
95% CI $\hat{\rho}$	{-0.773, -0.285}	{-0.829, -0.384}	{-0.783, -0.324}	{-0.770, -0.338}	{-0.781, -0.284}
Wald	14.33	18.50	15.86	14.92	16.99
P-value Wald	0.000	0.000	0.000	0.000	0.000
Rural sub-sample[c]					
$\hat{\delta}$	0.422	0.421	0.428	0.429	0.429
95% IC $\hat{\delta}$	{0.382, 0.461}	{0.378, 0.461}	{0.388, 0.466}	{0.388, 0.463}	{0.386, 0.466}
$\hat{\rho}$	-0.767	-0.766	-0.781	-0.783	-0.783
95% CI $\hat{\rho}$	{-0.826, -0.700}	{-0.831, -0.692}	{-0.841, -0.697}	{-0.847, -0.708}	{-0.849, -0.709}
Wald	180.17	179.77	202.93	203.98	206.34
P-value Wald	0.000	0.000	0.000	0.000	0.000

a. 95% confidence intervals of the estimated ATE and ρ in curly brackets. The number of Bayesian samples used to construct the confidence intervals is 1000.

The instrumental variables are described in Section 5.

b. Number of observations: sample of all children = 10650, urban sub-sample 3074, rural sub-sample 7576

The causal effect that is captured in this research is extremely higher than the effect that is captured in previous research that is available in the literature. Our results are produced after appropriate control for the endogeneity problem in the model and relaxing the restrictive parametric assumptions in the bivariate probit model. So, the captured effect in this research is distinguished and improved in terms of quality than that provided in the previous research in this field.

6. Conclusions and recommendations

This paper examines the impact of father unemployment on child school dropout using the National Baseline Household Survey (NBHS) in Sudan in 2009. School dropout is measured for children in the age group 6-15 years old. Child dropout decisions and father unemployment are both affected by unobserved confounders and are determined simultaneously in the model which generates an endogeneity bias in the treatment effect estimate. Accordingly, the traditional probit and logit models estimate the effect substantially biased toward zero. The paper uses a semi-parametric specification for the recursive bivariate probit model to estimate the causal effect of father unemployment on the propensity that children to dropout of school. The estimate is sensitive to the choice of the estimation method and the instrumental variables set that is used to control for the endogeneity problem. As in most research that uses survey data, finding suitable variables to serve as instruments in the model was a daunting process.

The estimated causal effect shows that father unemployment increases child school dropout by 28 percentage points on average. In the rural areas, the estimate is extremely higher, where it reaches 42 percentage points. This is a huge impact that has many severe consequences on the country's later economic performance and human capital development. This deterioration in the standard of living and the well-being of individuals was one of the factors that led to the Sudan revolution against dictatorship in 2019, 10 years after the NBHS-2009 survey was conducted. Sudan should make substantial reforms in the job-market regulations and structure and the policies related to job creation and protection. More importantly, however, Sudan needs to activate laws making basic education compulsory, build schools, reduce school costs and improve the education system structure. These are challenging in conflict areas, so having peace in the whole country is the first requirement to apply the suggestions in this paper.

For policymakers, this research quantifies the effect of father unemployment on child school dropout. It is very important to develop policies that reduce the causal effect of macroeconomic shock on enrolment in basic education. The education sector should be given permanent priority in all economic policies irrespective of the business cycle. The federal government should put a target enrolment rate in basic education and work closely with the local governments in achieving that targeted rate. Practitioners in the education sector need to develop methods to mitigate the effects of household shocks and policies that prevent students from dropping out of school. It is very important to conduct research to examine the after dropping out status, child labour and research to examine how dropped-out students can return to education and participate in human capital development in the country again. The generation of children that is covered in this survey are presumably workers in the job market now. The government needs to apply policies and conduct active labour market programs to improve the skills and knowledge of this generation, to compensate for the part of the training that was missed as a result of the education interruption. The government can launch large scheme re-training programs to attract the youth and young workers in the job market to increase their productivity, employability and job market opportunities.

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Appendix A

Table (A1): Independent Variables Description

Variable	Description
drop-out	child school dropout dummy
F. unemployed	father unemployment dummy
Age	child age in years
Male	child male dummy
HH members	number of household members
No. children	number of children in school age 6-16 in the household
Sh. education	share of per-capita education expenses from the total per-capita expenditures
Sh. house	share of house-related expenses
$\boldsymbol{log(exp)}$	log household per-capita total expenditures
Mother in HH	if the mother lives in the same household dummy
F. primary	father education level primary school/Kalwa dummy
F. secondary	father education level secondary dummy
Urban	urban dummy

Table (A2): Distribution of Father Education Level by Job-Market Status and by Urban and Rural

	mean	sd	Father job market status			
			Employed		Unemployed	
			mean	sd	mean	sd
Sample of all children						
No qualification	0.107	0.309	0.112	0.316	0.0848	0.279
Primary school/Kalwa[1]	0.329	0.470	0.331	0.471	0.321	0.467
Secondary	0.101	0.302	0.102	0.303	0.0992	0.299
Post-secondary/diploma.	0.035	0.185	0.0328	0.178	0.0465	0.211
University	0.006	0.077	0.006	0.078	0.005	0.072
Not stated	0.421	0.494	0.416	0.493	0.443	0.497
n	10,650		8,715		1,935	
Urban						
No qualification	0.104	0.306	0.109	0.312	0.0723	0.259
Primary school/Kalwa[1]	0.372	0.484	0.375	0.484	0.357	0.480
Secondary	0.187	0.390	0.184	0.387	0.212	0.409
Post-secondary/diploma	0.084	0.278	0.079	0.269	0.120	0.326
University	0.011	0.103	0.011	0.104	0.01	0.098
Not stated	0.241	0.428	0.243	0.429	0.229	0.421
n	3,074		2,659		415	
Rural						
No qualification	0.108	0.311	0.113	0.317	0.088	0.284
Primary school/Kalwa[1]	0.312	0.463	0.312	0.463	0.312	0.463
Secondary	0.067	0.249	0.066	0.248	0.068	0.253
Post-secondary/diploma	0.015	0.123	0.013	0.112	0.026	0.160
University	0.004	0.0628	0.004	0.063	0.004	0.063
Not stated	0.494	0.500	0.492	0.500	0.501	0.500
n	7,576		6,056		1,520	

Kalwa is a traditional religious school that teaches Quran and basic Arabic language and mathematics.

Table (A3): Marginal Effect Coefficients of the Probit and the Parametric Bivariate Probit Models for the Sample of all Children

	Probit	**IV1**	**IV2**	**IV3**	**IV4**	**IV5**
F. unemployed	0.024** (0.010)	0.247*** (0.061)	0.268*** (0.054)	0.290*** (0.055)	0.293*** (0.054)	0.301*** (0.050)
Age	-0.267*** (0.010)	-0.257*** (0.012)	-0.255*** (0.012)	-0.252*** (0.012)	-0.252*** (0.012)	-0.251*** (0.012)
Age sq.	0.012*** (0.000)	0.011*** (0.001)	0.011*** (0.001)	0.011*** (0.001)	0.011*** (0.001)	0.011*** (0.001)
Male	-0.061*** (0.008)	-0.057*** (0.008)	-0.056*** (0.008)	-0.055*** (0.008)	-0.055*** (0.008)	-0.055*** (0.008)
HH members	-0.014*** (0.002)	-0.015*** (0.002)	-0.015*** (0.002)	-0.015*** (0.002)	-0.015*** (0.002)	-0.015*** (0.002)
No. children	0.022*** (0.004)	0.025*** (0.004)	0.025*** (0.004)	0.025*** (0.004)	0.025*** (0.004)	0.025*** (0.004)
Sh. education	-0.033*** (0.003)	-0.031*** (0.003)	-0.031*** (0.003)	-0.031*** (0.003)	-0.031*** (0.003)	-0.031*** (0.003)
Sh. house	-0.005*** (0.001)	-0.005*** (0.001)	-0.005*** (0.001)	-0.005*** (0.001)	-0.005*** (0.001)	-0.005*** (0.001)
$\boldsymbol{log(exp)}$	-0.123*** (0.008)	-0.107*** (0.009)	-0.105*** (0.009)	-0.103*** (0.009)	-0.103*** (0.009)	-0.102*** (0.009)
Mother in HH	0.013 (0.023)	0.017 (0.023)	0.018 (0.023)	0.018 (0.023)	0.018 (0.023)	0.018 (0.023)
F. primary	-0.087*** (0.009)	-0.080*** (0.009)	-0.079*** (0.009)	-0.078*** (0.009)	-0.078*** (0.009)	-0.077*** (0.009)
F. secondary	-0.163*** (0.016)	-0.158*** (0.016)	-0.157*** (0.016)	-0.156*** (0.016)	-0.155*** (0.016)	-0.155*** (0.016)
Urban	-0.087*** (0.010)	-0.076*** (0.010)	-0.075*** (0.010)	-0.073*** (0.010)	-0.073*** (0.010)	-0.073*** (0.010)
log likelihood	-5024	-9701	-9695	-9694	-9694	-9689
$\hat{\rho}$		-0.436	-0.474	-0.514	-0.520	-0.535
se($\hat{\rho}$)		0.110	0.096	0.098	0.096	0.088
Sample size $n = 10650$**.**						

Table (A4): Marginal Effect Coefficients of the Probit and the Parametric Bivariate Probit Models for the Sub-Sample of Children in the Urban

	Probit	IV1	IV2	IV3	IV4	IV5
F. unemployed	0.015 (0.016)	0.199** (0.088)	0.218*** (0.068)	0.211*** (0.080)	0.210*** (0.081)	0.217*** (0.073)
Age	-0.225*** (0.015)	-0.228*** (0.015)	-0.228*** (0.015)	-0.228*** (0.015)	-0.228*** (0.015)	-0.228*** (0.015)
Age sq.	0.010*** (0.001)	0.010*** (0.001)	0.010*** (0.001)	0.010*** (0.001)	0.010*** (0.001)	0.010*** (0.001)
Male	-0.020* (0.011)	-0.020* (0.011)	-0.020* (0.011)	-0.020* (0.011)	-0.020* (0.011)	-0.020* (0.011)
HH members	-0.010*** (0.004)	-0.012*** (0.004)	-0.012*** (0.004)	-0.012*** (0.004)	-0.012*** (0.004)	-0.012*** (0.004)
No. children	0.010* (0.006)	0.013** (0.006)	0.013** (0.006)	0.013** (0.006)	0.013** (0.006)	0.013** (0.006)
Sh. education	-0.018*** (0.003)	-0.018*** (0.003)	-0.018*** (0.003)	-0.018*** (0.003)	-0.018*** (0.003)	-0.018*** (0.003)
Sh. house	-0.002 (0.002)	-0.002 (0.002)	-0.002 (0.002)	-0.002 (0.002)	-0.002 (0.002)	-0.002 (0.002)
$\boldsymbol{log(exp)}$	-0.093*** (0.012)	-0.091*** (0.012)	-0.091*** (0.012)	-0.091*** (0.012)	-0.091*** (0.012)	-0.091*** (0.012)
Mother in HH	-0.026 (0.036)	-0.021 (0.036)	-0.020 (0.036)	-0.020 (0.036)	-0.020 (0.036)	-0.020 (0.036)
F. primary	-0.048*** (0.012)	-0.047*** (0.012)	-0.047*** (0.012)	-0.047*** (0.012)	-0.047*** (0.012)	-0.047*** (0.012)
F. secondary	-0.082*** (0.017)	-0.083*** (0.017)	-0.083*** (0.017)	-0.084*** (0.017)	-0.084*** (0.017)	-0.083*** (0.017)
log likelihood	-961.7	-2044	-2040	-2039	-2039	-2038
$\hat{\rho}$		-0.534	-0.585	-0.567	-0.565	-0.585
se($\hat{\rho}$**)**		0.223	0.166	0.197	0.202	0.179
Sample size $n = 3074$.						

Table (A5): Marginal Effect Coefficients of the Probit and the Parametric Bivariate Probit Models for the Sub-Sample of Children in the Rural

	Probit	**IV1**	**IV2**	**IV3**	**IV4**	**IV5**
F. unemployed	0.022* (0.012)	0.220* (0.124)	0.238** (0.105)	0.299*** (0.073)	0.304*** (0.069)	0.307*** (0.065)
Age	-0.274*** (0.013)	-0.264*** (0.019)	-0.262*** (0.018)	-0.253*** (0.018)	-0.252*** (0.018)	-0.252*** (0.017)
Age sq.	0.012*** (0.001)	0.011*** (0.001)	0.011*** (0.001)	0.011*** (0.001)	0.011*** (0.001)	0.011*** (0.001)
Male	-0.080*** (0.010)	-0.074*** (0.011)	-0.074*** (0.011)	-0.070*** (0.010)	-0.070*** (0.010)	-0.070*** (0.010)
HH members	-0.016*** (0.003)	-0.016*** (0.003)	-0.016*** (0.003)	-0.016*** (0.003)	-0.016*** (0.003)	-0.016*** (0.003)
No. children	0.025*** (0.005)	0.028*** (0.005)	0.028*** (0.005)	0.028*** (0.005)	0.028*** (0.004)	0.028*** (0.004)
Sh. education	-0.039*** (0.005)	-0.037*** (0.005)	-0.037*** (0.005)	-0.036*** (0.005)	-0.036*** (0.005)	-0.036*** (0.005)
Sh. house	-0.007*** (0.002)	-0.006*** (0.002)	-0.006*** (0.002)	-0.006*** (0.002)	-0.006*** (0.002)	-0.006*** (0.002)
$\boldsymbol{log(exp)}$	-0.131*** (0.010)	-0.113*** (0.018)	-0.111*** (0.017)	-0.102*** (0.015)	-0.101*** (0.015)	-0.101*** (0.014)
Mother in HH	0.021 (0.028)	0.024 (0.028)	0.025 (0.028)	0.025 (0.028)	0.025 (0.028)	0.026 (0.028)
F. primary	-0.096*** (0.011)	-0.090*** (0.013)	-0.089*** (0.012)	-0.084*** (0.012)	-0.084*** (0.012)	-0.084*** (0.012)
F. secondary	-0.220*** (0.024)	-0.215*** (0.025)	-0.213*** (0.025)	-0.207*** (0.024)	-0.206*** (0.024)	-0.206*** (0.024)
log likelihood	-4007	-7539	-7535	-7533	-7533	-7530
$\boldsymbol{\hat{\rho}}$		-0.388	-0.426	-0.552	-0.564	-0.568
se($\boldsymbol{\hat{\rho}}$)		0.248	0.211	0.150	0.144	0.135
Sample size $\boldsymbol{n = 7576}$.						