RESEARCH REPORTS AND NOTES

HOUSEHOLD SHOCKS, CHILD LABOR, AND CHILD SCHOOLING

Evidence from Guatemala

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Abstract: Using data from the National Survey of Standards of Living conducted in Guatemala in 2000, this article tests the hypothesis that Guatemalan households use child labor and reduce child schooling to cope with household shocks. First, the authors use factor analysis to estimate the latent household propensity to natural disasters and socioeconomic shocks. Then, they estimate bivariate probit models to identify the determinants of child labor and schooling, including household propensity to natural disasters and socioeconomic shocks. Results suggest that households use child labor to cope with natural disasters and socioeconomic shocks. In contrast, the authors found no evidence that suggests that households reduce child schooling to cope with shocks. Findings also indicate that poor households are more likely to use child labor and schooling reduction as strategies to cope with socioeconomic shocks.

INTRODUCTION

Child labor affects the current and future welfare of children. In the short run, child labor exposes children to unsafe working environments and prevents normal child development. Child labor also reduces the time available for school and the quality of schooling (Binder and Scrogin 1999; Psacharopoulus 1997). Given that schooling is associated with poverty

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alleviation, disease reduction, and fertility choices (Glewwe 2002; World Bank 2005), child labor may have a negative impact on the welfare of children in the long run.[1]

Child labor has been traditionally considered a household response to income poverty (Amin, Quayes, and Rives 2004; Jensen and Nielsen 1997; Ray 2002) and labor market imperfections (Dumas 2007). A more recent strand of literature suggests that child labor is a household strategy to cope with natural disasters and socioeconomic shocks (Dendir 2007; Guarcello, Mealli, and Rosati 2003). Households may also reduce investments in a child's schooling to cope with household shocks (Jacoby and Skoufias 1997). Poor households are more likely to use child labor as a coping strategy given their lack of assets that could be used to recover from household shocks (Beegle, Dehejia, and Gatti 2006). Thus, the negative effect of such coping strategies on the current and future welfare of children is more significant among poor households.

This study tests the hypothesis that Guatemalan households use child labor and reduce child schooling to cope with natural disasters and socioeconomic shocks. We used factor analysis to estimate the latent household propensity to natural disasters and socioeconomic shocks based on information on household shocks included in the 2000 National Survey of Living Standards (Encuesta Nacional de Condiciones de Vida, or ENCOVI). This approach provides a stronger analytical framework to estimate shock indices than traditional methods such as binary variables and the total amount of reported shocks that do not account for measurement errors and restrict different household shocks to have similar effects. We then included estimated propensities in bivariate probit models to investigate the effect of natural disasters and socioeconomic shocks on child labor and schooling. We also analyzed differences in responses to household shocks among nonpoor, poor, and extremely poor. Results indicate that households tend to use child labor to cope with natural disasters and socioeconomic shocks. In contrast, we found no evidence that households reduce child schooling to cope with shocks. Findings also indicate that poor households are more likely to use child labor and schooling reduction as strategies to cope with socioeconomic shocks.

We have organized the rest of the article as follows: we first describe the background, then present the theoretical framework, describe the data and variables used in the study, present the econometric methodology, present the results, and finally provide conclusions.

1. An alternative view of child labor argues that children may benefit from work experience appropriate to their age. Benefits include human capital formation through work experience, as well as in-kind and money earnings. For a detailed discussion on the benefits of child labor, see Bourdillon (2006).

Table 1 Child Labor and Nonenrollment Ratios, by Region, Gender, and Area

	Child Labor				*Nonenrollment*			
	Boys		Girls		Boys		Girls	
Region	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban
Metropolitan	31.5	13.0	17.7	9.2	37.0	7.3	29.1	10.6
North	40.2	15.4	18.2	9.6	35.9	18.6	46.1	23.6
Northeast	25.8	14.7	6.9	9.6	29.9	10.8	31.2	16.1
Northwest	32.6	18.6	14.8	11.9	32.9	17.7	44.5	23.0
Central	34.6	21.8	17.9	22.7	28.9	14.8	31.8	17.9
Southeast	31.8	16.3	8.1	11.9	24.6	10.1	29.3	14.7
Southwest	30.1	23.7	18.3	12.0	22.5	16.7	33.7	20.1
Peten	33.0	23.6	8.6	13.0	31.7	18.7	35.3	15.9
Country	**32.9**	**18.0**	**14.8**	**12.4**	**29.4**	**14.0**	**36.7**	**17.5**

Note: We calculated these rates using the 2000 Encuesta Nacional de Condiciones de Vida (ENCOVI). The rates are expressed in percentages of children between five and sixteen years of age.

BACKGROUND

The incidence of child labor has gradually increased in Guatemala and is among the highest in Latin America (Guarcello et al. 2003). The International Labour Organization's International Programme for the Elimination of Child Labour (IPEC 2003) reports that 7.9 percent of children between seven and fourteen years of age worked for a salary or at home in 1994. This percentage increased to 23.5 percent in 2002. The average number of working hours per week was greater than thirty-five in all kinds of activities. Such large amounts of working hours may reduce the time available for child schooling. In addition, a significant number of children work in unsafe environments. According to the 2002 National Survey of Employment and Income (Encuesta Nacional de Empleo e Ingresos, or ENEI), at least 17,350 children worked in domestic jobs, 3,700 children worked in the fireworks industry, and 850 children worked collecting and sorting garbage. Other kinds of hazardous jobs included agriculture, mining and rock breaking, and sexual activities (IPEC 2003).

Table 1 presents the incidence of child labor by region, area, and gender for children between five and sixteen years old. The percentage of boys and girls working for a salary in rural areas is greater than in urban areas. The child labor rate is greater for boys than for girls in almost each stratum excluding urban areas in the Central region.[2] Boys in rural areas are more likely to work than are boys in urban areas. Although the rural

2. Guatemala is divided into eight political regions for sampling purposes: Metropolitan, Central, North, Southeast, Southwest, Northeast, Northwest, and Petén.

percentage of working girls is greater in the Metropolitan, North, Northwest, and Southwest regions, the urban percentage is greater in other regions. The maximum percentage of child labor is reported for boys in the Rural North region (40.2 percent). The minimum corresponds to girls in the Rural Northeast region (6.9 percent). Table 2 shows ethnic differentials in child labor. Indigenous children are more likely to work than are nonindigenous children in almost all regions, with the exception of the Southeast for boys and the Northeast and Petén for girls.

Educational indicators point to low levels of schooling. According to the World Bank (2003), the illiteracy rate in Guatemala was 31 percent in 2000. This rate is among the highest in Latin America, behind only Nicaragua and Haiti. On average, individuals older than fourteen years of age have 4.3 years of schooling. Table 1 shows that children in rural areas are less likely to attend school. In 2000, 29.4 percent of boys and 36.7 percent of girls between five and sixteen years old in rural areas were not enrolled in school. These percentages are greater than the urban percentages (14 percent for boys and 17.5 percent for girls). Nonenrollment ratios are greater for rural areas across all regions (see table 1).

Table 2 presents significant differences in nonenrollment ratios between indigenous and nonindigenous children. In 2000, more than 28 percent of indigenous boys were not enrolled in school, for a difference of 8.8 percent above nonindigenous boys. The difference between indigenous and nonindigenous girls is also substantial (16.3 percent). The nonenrollment ratios are less for indigenous boys only in the Central and Southeast regions. Indigenous girls are less likely to be enrolled in school than are nonindigenous girls in each region. However, the difference between indigenous and nonindigenous girls in the Central region seems to be minimal.

Demand-side factors seem to be very important for not enrolling children in school (see table 3). More than 30 percent of children out of school in rural and urban areas report income poverty as the main reason for not enrolling in school. The lack of interest in schooling is the second reason in urban areas and the third reason in rural areas. The second and third reasons for not enrolling boys and girls in school in rural areas are working for wages and working at home, respectively. Although factors associated with the supply of education were reported as reasons to not enroll in school, the low percentages of closed class, school distance, and no school in the community suggest that Guatemala has advanced significantly toward universal school coverage (World Bank 2005).

Guatemalan households are vulnerable to socioeconomic shocks such as job loss, inflation, business closure, decreases in international prices of produced goods, and crime, among others. Guatemala is also prone to natural disasters. According to Charvériat (2000), twenty-eight disasters occurred in Guatemala between 1979 and 1999, for an average of 0.9 disasters per year. Guatemala has the largest number of fatalities due to disasters

Table 2 Child Labor and Nonenrollment Ratios, by Region, Gender, and Ethnicity

	Child Labor				*Nonenrollment*			
	Boys		Girls		Boys		Girls	
Region	Indigenous	Non-indigenous	Indigenous	Non-indigenous	Indigenous	Non-indigenous	Indigenous	Non-indigenous
Metropolitan	37.8	16.8	31.5	10.4	40.0	9.2	38.9	10.4
North	39.5	27.8	20.5	12.6	33.8	19.9	45.1	20.8
Northeast	47.2	21.9	8.1	10.6	36.1	17.9	43.2	20.1
Northwest	38.6	26.1	18.3	14.0	30.7	24.1	42.9	28.8
Central	52.6	26.6	34.3	16.6	22.8	26.6	28.4	28.0
Southeast	22.2	30.8	18.5	11.5	16.7	19.4	25.9	23.9
Southwest	39.0	29.4	22.5	16.0	23.5	18.5	36.6	22.0
Peten	53.3	32.9	7.6	13.8	34.4	25.6	32.6	26.3
Country	**41.9**	**26.8**	**21.8**	**13.3**	**28.9**	**20.1**	**38.9**	**22.6**

Note: We calculated these rates using the 2000 Encuesta Nacional de Condiciones de Vida (ENCOVI). The rates are expressed in percentages of children between five and sixteen years of age.

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Table 3 Reason for Not Attending School, by Area and Gender

	Boys		*Girls*	
Reason	Rural	Urban	Rural	Urban
Illness	2.5	5.1	2.1	4.2
Closed Class	0.9	1.5	1.2	0.6
Working at Home	0.8	1.5	18.3	10.3
Working for Wage	25.9	15.0	7.7	8.5
Income Poverty	32.7	39.4	30.8	41.2
Not Interested	16.7	24.8	18.2	18.5
School Distance	1.9	—	3.5	1.5
Not School in the Community	2.2	—	2.2	0.9
Age	8.6	5.8	7.2	5.2
Other	7.8	6.9	8.8	9.1

Note: We calculated these rates using the 2000 Encuesta Nacional de Condiciones de Vida (ENCOVI). The rates are expressed in percentages of children between five and sixteen years of age.

in Central America, for a total of 24,139 people, or 2.2 fatalities per thousand habitants (based on the population in 1995). Estimated losses were more than US$3.062.5 billion or 17.3 percent of the gross domestic product (GDP) in 1995.[3] As a response to its propensity for natural disasters, Guatemala created the National Coordinator for Reduction of Disasters (Coordinadora Nacional para la Reducción de Desastres, or CONRED), which aims to reduce household vulnerability to natural disasters and coordinates national efforts during and after a disaster.[4]

THEORETICAL FRAMEWORK

Following Basu and Van (1998), parents are assumed to be benevolent and maximize the child's utility function $U = U(X, S, W)$, where X represents consumption greater than the minimum sustenance level, S is time available for schooling, and W is time available for child labor. The utility

3. Hurricane Stan is a more recent example of the vulnerability of Guatemala to natural disasters. The Economic Commission for Latin America and the Caribbean (2005) reported that Hurricane Stan affected 3.5 million people, or 34 percent of the population, in 2005. Direct effects were observed in more than 950 communities. More than 42,900 individuals had to live in temporary shelters. The losses were calculated at more than US$983 million, or 3.4 percent of the GDP in 2004.

4. Other official institutions that assist households in coping with household shocks include the Secretariat of Food Security, the Presidential Planning Secretariat, and the Ministry of Agriculture. Although the main focus of these institutions is on poverty alleviation, their actions may help reduce the propensity of child labor as a strategy to cope with household shocks.

function U is positively related to child consumption and schooling, and negatively related to child labor. That is,

$$\frac{\partial U}{\partial X} \geq 0, \frac{\partial U}{\partial S} \geq 0,$$

and

$$\frac{\partial U}{\partial W} \leq 0.$$

Parents' choices are subject to budget and time restrictions:

$$PX + P_s S \leq (Y - PX_0) + \omega W \quad (1a)$$

$$W + S \leq T \quad (1b)$$

where P is the price vector, P_S is the price of schooling, Y is the household income earned by adults, X_0 is the minimum household sustenance level, ω is the child wage, and T is the total amount of nonleisure time available for schooling and labor. This model is similar to the theoretical framework Ray (2002) used, with the difference being that parents are assumed to ensure a minimum level of sustenance for the household (i.e., X_0) rather than first choosing consumption for adults.

As a result of the maximization problem, assuming separability between child consumption and leisure, we derived the following simultaneous equations:

$$W^* = L(CH, FAM, COM, S^*, \omega, P_S, Y^*) \quad (2a)$$

$$S^* = L(CH, FAM, COM, W^*, \omega, P_S, Y^*) \quad (2b)$$

where *CH, FAM,* and *COM* are child, family, and community's characteristics, respectively. Y^* is equal to $Y - PX_0$, the disposable income for child consumption. W^* and S^* are the optimal choices on child labor and schooling, respectively.

The effects of child, family, and community characteristics on W^* and S^* depend on the type of such characteristics. Child ethnicity may have a negative impact on schooling, particularly if languages differ across ethnic groups and education is not provided in such languages. There is also evidence that suggests that mothers have stronger preferences for child schooling than fathers (Ridao-Cano 2001) and that households may treat boys and girls differently (Binder 1998; Emerson and Portela Souza 2007). Size imposes larger costs on the household and therefore may reduce schooling and increase child labor (Patrinos and Psacharopoulos 1997). Households in more developed communities have more access to public schools, which would increase schooling rates. The development of labor

markets in such communities may be another factor affecting child labor choices.

Because nonleisure time T is fixed, an increase (decrease) in time allocated to child labor will decrease (increase) the time allocated to schooling. This implies that child labor and schooling are substitutes; therefore, we expected their effect on each other to be negative. That is,

$$\frac{\partial S^*}{\partial W^*} \leq 0,$$

and

$$\frac{\partial W^*}{\partial S^*} \leq 0.$$

We expected negative price effects on schooling. In contrast, because child labor is considered to decrease child utility, we expected price effects on child labor to be positive. Thus, expected price effects are as follows:

$$\frac{\partial S^*}{\partial \omega} \leq 0, \frac{\partial S^*}{\partial Ps} \leq 0, \frac{\partial W^*}{\partial \omega} \geq 0, \text{and } \frac{\partial W^*}{\partial Ps} \geq \dot{0}.$$

Under the benevolent-parents assumption, we expected disposable income to have a positive effect on child schooling and a negative effect on child labor. That is,

$$\frac{\partial S^*}{\partial Y^*} \geq 0,$$

and

$$\frac{\partial W^*}{\partial Y^*} \leq 0.$$

It is worth noting that household shocks (e.g., natural disasters, socioeconomic shocks) may decrease household income from adults. In addition, household survival expenditures (e.g., health costs) may increase as a result of household shocks (Del Ninno and Marini 2005). Parents may send children to work to compensate for income losses and to pay for survival expenditures. In addition, parents may not have enough income to enroll children in school. Poor households are more likely to implement such coping strategies because they usually lack other assets to cope with household shocks. Given this potential household behavior to cope with shocks, and to structure the analysis, we tested the following hypotheses:

H_1: *Natural disasters and socioeconomic shocks increase the time allocated to child labor.*

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H_2: *Natural disasters and socioeconomic shocks decrease the time allocated to child schooling.*

H_3: *The impact of natural disasters and socioeconomic shocks is more significant among poor households.*

DATA AND VARIABLES

In 2000, Guatemala implemented a living standards measurement survey referred to as Encuesta Nacional de Condiciones de Vida 2000 (ENCOVI). The ENCOVI followed a two-stage stratified cluster sampling design. The stratification consists of rural and urban areas in eight political regions, for a total of sixteen areas. Households in these areas are classified in three strata: high, medium, and low income. A total of 11,170 rural and urban sectors are the primary sampling units (PSUs). In the first stage, the sampling probability is the same for each PSU. The second stage, in which households were the secondary sampling units (SSUs), implemented systematic sampling. Groups of twelve and six households were formed for rural and urban areas, respectively. Finally, 7,276 households provided the information that ENCOVI presented. We selected a subsample of 7,332 children between five and sixteen years to conduct this study.

The ENCOVI includes information on child activities and binary indicators for household shocks. That information is used to define child labor as children working at least one hour in the market for a monetary compensation. Households were also asked whether they experienced any of the shocks listed in the questionnaire over the previous twelve months (the appendix here presents the questions in Spanish). The list of shocks included natural disasters such as earthquakes, droughts, floods, storms, hurricanes, plagues, landslides, forest fires, and loss of harvest. The questionnaire also included socioeconomic shocks: loss of employment of any member; lowered income of any member; bankruptcy of family business; illness or serious accident of a working member of the household; death of working member of the household; abandonment by the household head; fire in the house, business, or property; criminal act; land dispute; loss of cash or in-kind assistance; fall in prices of products in the household business, business closing; massive layoffs; and general price increases. Household propensity to natural disasters and socioeconomic shocks may influence the incidence of shocks.

About 28 percent of the sampled households suffered at least one natural disaster, and almost 70 percent reported at least one socioeconomic shock. The most reported socioeconomic shocks are general increase in prices, illness or serious accident of a working member of the household, lowered income of any member, and loss of employment of any member. Correlation estimates are less than 0.2 for most pairs of shocks, with the exception of the correlation between plague and losts of harvest (0.27),

Table 4 Definition of Variables

Variables	*Definition*	*Mean*	*SD*	*Min.*	*Max.*
SCHOOLING	Is child schooling? (yes = 1; no = 0)	0.738	0.439	0	1
WORKING	Is child working? (yes = 1; no = 0)	0.207	0.404	0	1
HHSHOCK	Number of negative events in past 12 months	1.631	1.454	0	14
NATDIS	Household propensity to natural disasters	0	0.697	−0.420	7.551
SOCECON	Household propensity to socioeconomic shocks	0	0.685	−0.455	7.087
EXTPOOR	Is the household below the extreme poverty line? (yes = 1; no = 0)	0.179	0.384	0	1
POOR	Is the household below the poverty line? (yes = 1; no = 0)	0.449	0.497	0	1
AGE	Child age	10.155	3.421	5	16
MALE	Child gender (male =1; female = 0)	0.510	0.500	0	1
INDIGENOUS	Child ethnic (indigenous = 1; otherwise = 0)	0.410	0.490	0	1
MOEDUC	Did mother complete elementary school? (yes = 1; no = 0)	0.118	0.323	0	1
FAEDUC	Did father complete elementary school? (yes = 1; no = 0)	0.154	0.361	0	1
REMITT	The log of household income (in thousands of quetzals) from remittances	1.077	2.259	0	12.430
HEADMALE	Is the household head male? (yes = 1; no = 0)	0.849	0.358	0	1
HHSIZE	Number of household members	7.043	2.419	2	18
RURAL	Child location (urban = 0; rural = 1)	0.616	0.486	0	1
NORTH	Does child live in this region? (yes = 1; no = 0)	0.120	0.320	0	1
NORTHEAST	Does child live in this region? (yes = 1; no = 0)	0.070	0.260	0	1
SOUTHEAST	Does child live in this region? (yes = 1; no = 0)	0.110	0.310	0	1
CENTRAL	Does child live in this region? (yes = 1; no = 0)	0.170	0.370	0	1
SOUTHWEST	Does child live in this region? (yes = 1; no = 0)	0.170	0.380	0	1
NORTHWEST	Does child live in this region? (yes = 1; no = 0)	0.190	0.390	0	1
PETEN	Does child live in this region? (yes = 1; no = 0)	0.090	0.290	0	1

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business closing and massive layoffs (0.23), and loss of employment of any member and lowered income of any member (0.3).

Table 4 presents the definition and descriptive statistics of the variables used in this study. The variables include indicators for extreme poverty (*EXTPOOR*) and general poverty (*POOR*). The National Institute of Statistics calculated the poverty indicators using the per capita consumption approach. The extreme poverty line (1,911 quetzals per year) consisted of expenditures needed to cover the minimum amount of calories needed to survive. The general poverty line (4,318 quetzals per year) covered nonnutritious expenditures as well.[5] Other variables used in the study include child characteristics (*AGE, MALE,* and *INDIGENOUS*), family characteristics including mother's and father's education, gender of the household head, and household size (*MOEDUC, FAEDUC, HEADMALE,* and *HHSIZE*, respectively), and location variables (*URBAN, NORTH, NORTHEAST, SOUTHEAST, CENTRAL, SOUTHWEST, NORTHWEST,* and *PETEN*).

ECONOMETRIC METHODOLOGY

The information included in ENCOVI can be used in different ways to investigate the effects of household shocks on child labor and schooling. For instance, Guarcello and colleagues (2003) used the information to estimate the effects of individual and collective household shocks on child labor. They used binary indicators to classify a household as hit by a shock if the household reported at least one shock. Although this approach is suitable for measuring shock incidence, it ignores the propensity to household shocks and assumes that the effect of being affected by one or more shocks is the same. Counting the shocks a household has suffered may be an alternative to account for the occurrence of various shocks. This approach, however, assumes that different shocks have the same effect on child labor and schooling.[6]

This article proposes a different approach to measure the propensity to household shocks. First, we classified reported household shocks as natural disasters and socioeconomic shocks. Then, we estimated two indices to measure the propensity to natural disasters and socioeconomic shocks using factor analysis. We assumed the unobserved household propensity to natural disasters and socioeconomic shocks influenced reported shocks as follows:

$$ND_i = \lambda_i NATDIS + e_i \tag{3a}$$

$$SE_j = \lambda_j SOCECON + e_j \tag{3b}$$

5. Using an exchange rate of 7.50 quetzals per U.S. dollar, the poverty and extreme poverty lines are equivalent to $575.73 and $254.80, respectively.

6. We thank an anonymous reviewer for addressing this limitation of counting household shocks.

where *NDi* is an indicator that takes the value of one if the household experienced natural disaster *i* (e.g., earthquakes, droughts, floods) and zero otherwise. Similarly, the indicator *SEj* takes the value of one if the household was hit by socioeconomic shock *j* (e.g., loss of employment of any member, lowered income of any member, bankruptcy of family business) and zero otherwise. The factors *NATDIS* and *SOCECON* are unobserved common factors that influence the incidence of natural disasters and socioeconomic shocks, respectively. Coefficients λ_i and λ_j represent the factor loadings relating indicators ND_i and SE_j to latent factors *NATDIS* and *SOCECON*, respectively. The terms e_i and e_j represent the variance that is unique to indicators ND_i and SE_j, respectively, and are independent of the corresponding factors and all other e_l.

Factor analysis provides a stronger analytical framework to estimate shock indices than do traditional methods such as binary variables representing shock incidence and the total amount of reported shocks. First, factors can be used as proxies for latent variables, which are unobservable and inestimable using traditional methods. Therefore, *NATDIS* and *SOCECON* can be interpreted as the latent household propensity to natural disasters and socioeconomic shocks, respectively. Second, *NATDIS* and *SOCECON* do not restrict different household shocks to equally affect child labor and schooling, given that factor loadings are allowed to vary across shock indicators. Finally, factor analysis provides estimates that are adjusted for measurement error, which traditional methods ignore (Brown 2006).

To investigate the impact of natural disasters and socioeconomic shocks on child labor and schooling, we modeled the optimal choice of child schooling and labor under the assumption that Equations 2a and 2b follow a linear form:

$$S^* = X\,\beta_s + u_s \tag{4a}$$

$$W^* = X\,\beta_w + u_w \tag{4b}$$

where S^* and W^* represent the optimal time allocated to child schooling and labor, respectively. Vector X represents determinants of child schooling and labor including child, family, and community characteristics, as well as the shock indices *NATDIS* and *SOCECON*. Vectors β_s and β_w include the parameters to be estimated. Finally, u_s and u_w are error terms that follow a normal joint distribution with mean zero and the same variance for each child. The error terms u_s and u_w are allowed to be correlated to control for potential endogeneity between child schooling and labor.

Vector X includes *AGE*, *MALE*, and *INDIGENOUS* to control for child characteristics. Because of potential nonlinear age effects, we also included age square (*AGESQ*). We included *MOEDUC*, *FAEDUC*, *HEADMALE*, and *HHSIZE* to control for family characteristics, and *REMITT* to measure the

effect of remittances on child labor and schooling. We included *RURAL* and regional dummy variables to control for unobserved community characteristics. Regional dummy variables are *NORTH, NORTHEAST, SOUTHEAST, CENTRAL, SOUTHWEST, NORTHWEST,* and *PETEN. METROPOLITAN* is the base region.

Unfortunately, we could not estimate Equation 4á because ENCOVI did not report the time allocated to child schooling. Alternatively, ENCOVI included an indicator on child enrollment in school. Therefore, we replaced S^* and W^* with *Schooling* and *Working*, respectively. The indicator *Schooling* is equal to one when the optimal allocation of time to child schooling is greater than zero ($S^* > 0$) and zero otherwise. Similarly, *Working* is an indicator equal to one when the optimal allocation of time to child labor is greater than zero ($W^* > 0$) and zero otherwise. The result of this transformation is a bivariate probit model.

We estimated bivariate probit models including *NATDIS* and *SOCECON* to test H1 and H2. Using these factors to estimate the bivariate probit models allowed us to assess the individual effects of household propensity to natural disasters and socioeconomic shocks on child labor and schooling. We also included the interaction of *NATDIS* and *SOCECON* with the poverty indices *POOR* and *EXTPOOR* to test H3.

EMPIRICAL RESULTS

Table 5 presents the estimation results of Equations 3a and 3b. Shock indicators are assumed to be affected by factors *NATDIS* and *SOCECON* if their corresponding Kaiser-Meyer-Olkin (KMO) statistic is greater than 0.5. Nine indicators on natural disasters are identified to be related to *NATDIS* and 14 indicators on socioeconomic shocks are related to *SOCECON*. Plagues and loss of harvest show the highest factor loadings (0.406), followed by droughts and storms. The lower factor loading corresponds to reports on earthquakes (0.154). The highest factor loading for *SOCECON* corresponds to lowered income of any member (0.456), followed by massive layoffs (0.422). The lowest factor loading corresponds to death of working member. We used corresponding factor loadings to estimate *NATDIS* and *SOCECON*, which we then included in probit models to investigate the effect of natural disasters and socioeconomic shocks on child labor and schooling.

Table 6 presents the estimation results (i.e., marginal effects) of bivariate probit models, including the effects of natural disaster (*NATDIS*) and socioeconomic shocks (*SOCECON*) on child labor and schooling. In support of H1, the estimated marginal effects of *NATDIS* and *SOCECON* on the probability of child labor (*WORKING*) are positive and significant in Models 1, 3 and 5. This indicates that households use child labor to cope with natural disasters and socioeconomics shocks. These findings are

Table 5 Factor Analysis of Natural Disasters and Socioeconomic Shocks

NATDIS			*SOCECON*		
Variables	Factor loadings	KMO statistic	Variables	Factor loadings	KMO statistic
Plagues	0.406	0.656	Lowered income of any member	0.456	0.619
Loss of harvest	0.406	0.652	Massive layoffs	0.422	0.601
Droughts	0.370	0.712	Loss of employment of any member	0.313	0.622
Storms	0.354	0.712	Business closing	0.286	0.609
Landslides	0.293	0.692	General increase in prices	0.239	0.667
Hurricanes	0.287	0.679	Bankruptcy of family business	0.237	0.603
Floods	0.214	0.643	Illness or accident of working member	0.183	0.655
Forest fires	0.209	0.695	Fall in prices of products in business	0.163	0.536
Earthquakes	0.154	0.617	Loss of cash or in-kind assistance	0.153	0.624
			Criminal act	0.138	0.674
			Land dispute	0.110	0.603
			Abandonment by the household head	0.085	0.566
			Fire in the house/ business/ property	0.049	0.537
			Death of working member	0.044	0.576

consistent with existing evidence from developing country contexts (e.g., Beegle et al. 2006). Although the marginal effects of *NATDIS* are greater than 0.02, the effects of *SOCECON* are less than 0.02. This suggests that child labor is more responsive to natural disasters than to socioeconomic shocks.

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Table 6 Marginal Effects on Child Labor and Schooling

	Model 1		*Model 2*		*Model 3*		*Model 4*		*Model 5*		*Model 6*	
	Schooling	Working	Schooling	Working	Schooling	Working	Schooling	Working	Schooling	Working	Schooling	Working
NATDIS	0.017	0.023	−0.008	0.040	—	—	—	—	0.018	0.020	−0.015	0.041
	(0.007)**	(0.007)***	(0.014)	(0.014)***					(0.007)**	(0.007)***	(0.014)	(0.014)***
NATDIS × EXTPOOR	—	—	0.002	−0.035	—	—	—	—	—	—	0.009	−0.036
			(0.020)	(0.019)*							(0.020)	(0.019)*
NATDIS × POOR	—	—	0.046	−0.017	—	—	—	—	—	—	0.058	−0.025
			(0.017)***	(0.016)							(0.017)***	(0.017)
SOCECON	—	—	—	—	−0.000	0.019	0.024	−0.000	−0.005	0.014	0.027	−0.007
					(0.008)	(0.008)**	(0.012)**	(0.011)	(0.008)	(0.008)*	(0.012)**	(0.012)
SOCECON × EXTPOOR	—	—	—	—	—	—	−0.017	0.009	—	—	−0.021	0.012
							(0.027)	(0.025)			(0.027)	(0.025)
SOCECON × POOR	—	—	—	—	—	—	−0.045	0.042	—	—	−0.059	0.043
							(0.016)***	(0.016)***			(0.016)***	(0.016)***
AGE	0.251	0.085	0.251	0.084	0.251	0.085	0.251	0.085	0.251	0.084	0.250	0.084
	(0.015)***	(0.017)***	(0.015)***	(0.017)***	(0.015)***	(0.017)***	(0.015)***	(0.017)***	(0.015)***	(0.017)***	(0.015)***	(0.017)***
AGESQ	−0.012	−0.001	−0.012	−0.001	−0.012	−0.001	−0.012	−0.001	−0.012	−0.001	−0.012	−0.001
	(0.001)***	(0.001)*	(0.001)***	(0.001)	(0.001)***	(0.001)*	(0.001)***	(0.001)*	(0.001)***	(0.001)*	(0.001)***	(0.001)*
MALE	0.060	0.182	0.060	0.182	0.059	0.182	0.059	0.182	0.060	0.182	0.060	0.182
	(0.009)***	(0.010)***	(0.009)***	(0.010)***	(0.009)***	(0.010)***	(0.009)***	(0.010)***	(0.009)***	(0.010)***	(0.009)***	(0.010)***
INDIGENOUS	−0.038	0.098	−0.038	0.098	−0.037	0.102	−0.037	0.102	−0.039	0.099	−0.039	0.099
	(0.011)***	(0.012)***	(0.011)***	(0.012)***	(0.011)***	(0.012)***	(0.011)***	(0.012)***	(0.011)***	(0.012)***	(0.011)***	(0.012)***
MOEDUC	0.185	−0.091	0.184	−0.090	0.0185	−0.092	0.185	−0.093	0.185	−0.091	0.184	−0.090
	(0.015)***	(0.020)***	(0.015)***	(0.020)***	(0.015)***	(0.196)***	(0.014)***	(0.019)***	(0.014)***	(0.020)***	(0.014)***	(0.020)***
FAEDUC	0.172	−0.042	0.171	−0.042	0.172	−0.042	0.171	−0.041	0.172	−0.042	0.170	−0.040
	(0.013)***	(0.019)**	(0.013)***	(0.019)**	(0.013)***	(0.019)**	(0.013)***	(0.019)**	(0.013)***	(0.019)**	(0.013)***	(0.019)**
REMITT	0.012	0.002	0.012	0.002	0.013	0.002	0.013	0.002	0.013	0.002	0.012	0.002
	(0.003)***	(0.003)	(0.003)***	(0.003)	(0.003)***	(0.003)	(0.003)***	(0.003)	(0.003)***	(0.003)	(0.003)***	(0.003)
HEADMALE	0.039	0.019	0.043	0.021	0.041	0.021	0.040	0.022	0.038	0.019	0.042	0.021
	(0.052)	(0.048)	(0.052)	(0.048)	(0.052)	(0.047)	(0.052)	(0.047)	(0.052)	(0.048)	(0.053)	(0.048)
HHSIZE	−0.008	0.005	−0.008	0.005	−0.008	0.005	−0.007	0.005	−0.008	0.005	−0.008	0.005
	(0.002)***	(0.002)**	(0.002)***	(0.002)**	(0.002)***	(0.002)**	(0.002)***	(0.002)**	(0.002)***	(0.002)**	(0.002)***	(0.002)**

(*continued*)

Table 6 (continued)

	Model 1		*Model 2*		*Model 3*		*Model 4*		*Model 5*		*Model 6*	
	Schooling	Working	Schooling	Working	Schooling	Working	Schooling	Working	Schooling	Working	Schooling	Working
RURAL	−0.103	0.081	−0.103	0.080	−0.099	0.088	−0.099	0.088	−0.103	0.083	−0.103	0.082
	(0.011)***	(0.011)***	(0.010)***	(0.011)***	(0.011)***	(0.011)***	(0.010)***	(0.011)***	(0.011)***	(0.011)***	(0.011)***	(0.011)***
NORTH	−0.063	0.013	−0.060	0.011	−0.063	0.018	−0.061	0.016	−0.064	0.017	−0.057	0.012
	(0.030)**	(0.026)	(0.030)**	(0.026)	(0.030)**	(0.026)	(0.030)**	(0.026)	(0.030)**	(0.026)	(0.030)*	(0.026)
NORTHEAST	−0.028	0.003	−0.022	−0.000	−0.027	0.010	−0.026	0.009	−0.029	0.007	−0.021	0.001
	(0.031)	(0.030)	(0.031)	(0.030)	(0.031)	(0.030)	(0.031)	(0.030)	(0.031)	(0.030)	(0.031)	(0.030)
SOUTHEAST	−0.001	0.025	0.003	0.023	0.001	0.034	0.001	0.035	−0.003	0.029	0.002	0.027
	(0.026)	(0.027)	(0.026)	(0.027)	(0.026)	(0.028)	(0.026)	(0.028)	(0.027)	(0.027)	(0.026)	(0.027)
CENTRAL	−0.020	0.087	−0.017	0.086	−0.019	0.086	−0.017	0.084	−0.019	0.086	−0.013	0.081
	(0.026)	(0.028)***	(0.026)	(0.028)***	(0.026)	(0.028)***	(0.026)	(0.028)***	(0.026)	(0.028)***	(0.026)	(0.028)***
SOUTHWEST	−0.008	0.013	−0.005	0.010	−0.007	0.019	−0.007	0.019	−0.009	0.016	−0.005	0.013
	(0.026)	(0.025)	(0.026)	(0.025)	(0.025)	(0.025)	(0.026)	(0.025)	(0.026)	(0.025)	(0.026)	(0.025)
NORTHWEST	−0.064	−0.015	−0.060	−0.017	−0.064	−0.008	−0.063	−0.009	−0.066	−0.011	−0.060	−0.014
	(0.028)**	(0.024)	(0.028)**	(0.024)	(0.028)**	(0.024)	(0.028)**	(0.024)	(0.028)**	(0.024)	(0.028)**	(0.024)
PETEN	−0.054	0.036	−0.052	0.033	−0.049	0.046	−0.049	0.047	−0.056	0.039	−0.052	0.037
	(0.031)*	(0.029)	(0.030)*	(0.029)	(0.030)	(0.030)	(0.030)	(0.030)	(0.031)*	(0.029)	(0.031)*	(0.029)
ρ	−0.2696	−0.2702	−0.2660	−0.2652	−0.2695	−0.2690						
	(0.0235)***	(0.0235)***	(0.0235)***	(0.235)***	(0.0234)***	(0.0235)***						
Observations	7332	7332	7332	7332	7332	7332						
Log Pseudo-Likelihood	−6634.48		−6627.02		−6641.81		−6635.00		−6632.74		−6616.48	
Akaike Information Criterion	13,346.95		13,340.04		13,361.62		13,356.00		13,347.49		13,330.96	
Prob. > χ^2	0.0000		0.0000		0.0000		0.0000		0.0000		0.0000	

*p < .10; **p < .05; ***p < .01

We found no evidence to support H2. Socioeconomic shocks seem to have no effect on child schooling, as indicated by insignificant coefficients of *SOCECON* for the schooling equation in Models 3 and 5. In contrast to H2, the marginal effect of *NATDIS* on child schooling is positive and significant in Models 1 and 2. This suggests that child schooling increases with natural disasters, which contradicts the hypothesis that households transfer resources from schooling to survival expenditures, which usually increase with household shocks by not enrolling children in school. However, this result is consistent with the evidence Duryea and Arends-Kuenning (2003) presented, which suggests that schooling can increase under bad macroeconomic conditions because child labor is less attractive as a result of falls in wages for unskilled labor. Both child labor and schooling may increase if natural disasters affect domestic production and, in turn, increase the time available for these child activities.

In support of H3, estimated coefficients on *SOCECON* × *POOR* in Models 4 and 6 indicate that poor households are more likely to use child labor as a strategy to cope with socioeconomic shocks than are nonpoor households. The coefficients also indicate that poor households reduce child schooling to cope with socioeconomic shocks, which is consistent with the evidence Jacoby and Skoufias (1997) presented. In contrast, estimated coefficients on *NATDIS* × *POOR* in Models 2 and 6 suggest that natural disasters increase child schooling in poor households but not in extremely poor and nonpoor households, which contradicts H3. Also, we found no evidence to support the hypothesis that extremely poor households respond differently to socioeconomic shocks in terms of child labor and schooling compared with nonpoor households. Compared with nonpoor households, extremely poor households are also less likely to use child labor for coping with natural disasters, as indicated by estimated coefficients of *NATDIS* × *EXTPOOR* in Models 2 and 4. Extremely poor households may have limited access to labor markets; consequently, child labor would not be a potential strategy to cope with natural disasters or socioeconomic shocks.

In addition, results suggest that child characteristics affect child labor and schooling (see table 6). The probability of child labor and schooling increases with age at a decreasing rate. This suggests a lower probability of enrolling in middle school, at least in normative age. In addition, the probability of child labor and schooling is greater for boys than for girls. That is, households may treat boys and girls differently in terms of child labor and schooling (Binder 1998; Emerson and Portela Souza 2007). Boys are more likely to attend school than girls. However, boys are also more likely to be sent to the labor market. Ethnicity also seems to affect child labor and schooling. Indigenous children are more likely to work than nonindigenous children and less likely to study. McEwan and Trow-

bridge (2007) also have presented evidence on the schooling differentials between indigenous and nonindigenous children in Guatemala.

Parents with at least primary education increase the probability of child schooling. In contrast, the probability of child labor decreases with the education of both mothers and fathers. These effects are more significant for mothers than for fathers, in support of the hypothesis that mothers have a stronger preference for child welfare (Ridao-Cano 2001). Educated parents usually earn higher wages, which may be enough to pay for survival expenditures. In that case, child labor is not needed to ensure household survival and children may be enrolled in school. Consistent with previous findings (e.g., Patrinos and Psacharopoulos 1997), household size (*HHSIZE*) negatively affects the probability of schooling and increases the probability of child labor. In contrast, remittances increase the probability of schooling. However, remittances do not affect the probability of child labor. This indicates that remittances do not completely eliminate child labor, although the number of working hours could be reduced. This is consistent with our theoretical framework, which predicts that more adult income reduces the number of hours allocated to child labor and increases the time allocated to schooling.

Table 6 also shows that children in rural areas are less likely to be enrolled in school compared with children in urban areas. As table 3 shows, households in rural areas point to income poverty, paid work, and lack of interest as primary reasons for not sending children to school. Children in rural areas are also more likely to work, as the positive and significant coefficients of *RURAL* indicate in the working equations. Compared with the metropolitan area, children are more likely to work in the Central region, where labor markets are more developed. In addition, the probability of schooling is lower in the North, Northwest, and Petén, which are regions with a significant indigenous population.

Finally, it is worth noting that the correlation (ρ) between *schooling* and *working* is negative and significant across all models, greater than 0.26 in absolute terms (see table 6). This is consistent with the theoretical framework of this study and existing evidence (e.g., Binder and Scrogin 1999) that suggests a trade-off between child labor and schooling.

CONCLUSION AND POLICY RECOMMENDATION

This article investigates whether Guatemalan households use child labor and reduce child schooling to cope with natural disasters and socioeconomic shocks. Findings indicate that households tend to use child labor to cope with natural disasters and socioeconomic shocks. In contrast, we found no evidence that households reduce child schooling to cope with such shocks. Moreover, findings suggest that child schooling

increases with natural disasters. Both child labor and schooling may be expected to increase with natural disasters if domestic production is affected and if the time available for working and schooling consequently increases.

Results also indicate that poor households (but not extremely poor households) are more likely to use child labor and schooling reduction as strategies to cope with socioeconomic shocks. As a response to such shocks, poor households may have to send children to labor markets. They may use child earnings to pay for survival expenditures, especially when adult income decreases as a result of socioeconomic shocks (Beegle et al. 2006). In addition, households may reallocate resources to survival expenditures by not enrolling children in school. In contrast, we found no evidence that poor and extremely poor households are more likely to use child labor to cope with natural disasters than are nonpoor households. In contrast, findings indicate that extremely poor households are less likely to use this strategy than are nonpoor households. Natural disaster may further restrict access to labor markets for extremely poor households, which would prevent them from using child labor to cope with natural disasters and socioeconomic shocks.

Child labor and schooling reduction may increase the amount of resources aimed at mitigating the negative effects of socioeconomic shocks (Jacoby and Skoufias 1997). However, such coping strategies may have a negative impact on the current and future welfare of children. The current welfare of children may be put at risk because of unsafe working environments. The reduction in the amount and quality of schooling—given that more schooling is associated with poverty alleviation, disease reduction, and fertility choices—also jeopardizes the future welfare of children (Glewwe 2002; World Bank 2005).

Public policies aimed to prevent and mitigate socioeconomic shocks may improve the welfare of children. For example, coping assistance programs could be implemented to provide households with access to credit, insurance, and assets to cope with socioeconomic shocks (Beegle et al. 2006; Guarcello et al. 2003). Mitigation policies could be attached to schooling; thus, households would send their children to school to improve the future welfare of children and to be eligible for coping assistance. Implementing coping assistance programs may be a challenge in developing countries. Guatemala may face this challenge using official institutions such as the Secretariat of Food Security, the Presidential Planning Secretariat, and the Ministry of Agriculture, which have already implemented poverty alleviation and food security programs. Child labor and schooling reduction would not be used as coping strategies if similar programs are implemented to assist households recovering from negative shocks.

APPENDIX A.

QUESTIONS USED TO ESTIMATE THE LATENT FACTORS *NATDIS* AND *SOCIOECON*

- En los últimos 12 meses ¿el hogar se ha visto afectado por alguno de los siguiente problemas de tipo general?

1. Terremoto
2. Sequía
3. Inundación
4. Tormentas
5. Huracán
6. Plagas
7. Deslizamiento de tierras
8. Incendios forestales
9. Cierre de empresas
10. Despidos masivos
11. Aumento general de precios
12. Protestas públicas
13. Otro, ¿cuál?

- En los últimos 12 meses, ¿este hogar se vio afectado por alguno o algunos de los siguiente problemas?

1. Pérdida del empleo de algún miembro
2. Baja de ingresos de algún miembro del hogar
3. Quiebra del negocio familiar
4. Enfermedad o accidente grave de algún trabajador miembro del hogar
5. Muerte de un trabajador miembro del hogar
6. Muerte de otro miembro del hogar
7. Abandono del jefe de hogar
8. Incendio de la vivienda/negocio/propiedad
9. Hecho delictivo
10. Disputa de tierras
11. Disputas familiares
12. Pérdida de ayudas en dinero o especie
13. Caída de los precios de los productos del negocio del hogar
14. Pérdida de la cosecha
15. Otros, ¿cuáles?

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