THE EFFECT OF SCHOOL DAMAGES ON EDUCATIONAL OUTCOMES IN POST-HURRICANE JAMAICA

Kaywana Raeburn[1]

Abstract

Households and individuals in developing countries are faced with a multitude of risks which can cause severe variability in current income and affect investment in human capital. In Latin America and the Caribbean, some of the major sources of such risk are natural disasters which occur on a regular basis. In this paper, I investigate the effect of a widespread unanticipated shock, a hurricane, on the investment in child human capital in Jamaica. Specifically, I analyse the impact of hurricane Ivan (2004) on two educational indicators among school-aged children in Jamaica using data from the Jamaica Survey of Living Conditions (JSLC), and data on damages to schools due to the hurricane at the parish level. Preliminary results suggests that the passage of hurricane Ivan had no effect on the probability of attending school for 13 to 16 year olds and a negative effect on the number of days attended school for 13 to 16 year old girls from rural and other town areas.

Keywords: Natural Disasters; Education; Caribbean

JEL: I21; Q54

[1] Kaywana Raeburn is a Ph.D. candidate in the Department of Economics at McGill University, Montreal, Canada.

1. INTRODUCTION

Households and individuals in developing countries are faced with a multitude of risks which can cause variability in income and consumption (Dercon, 2002). In Latin America and the Caribbean, some of the major sources of such risks are natural disasters such as earthquakes, tropical storms, hurricanes, volcanic eruptions and floods. The Caribbean islands in particular are extremely vulnerable to hurricanes because of their geographic location and small sizes. The macroeconomic damages resulting from a single disaster is often substantial and the impact of on household welfare is complex as it can affect various factors that contribute to welfare: household income, household assets and the physical well-being of household members. Outcomes for individual household members can deteriorate if income and asset shortfall limits the resources available for investment in human capital production. Additionally injuries and loss of life negatively affect productive capacity and can permanently reduce household welfare through loss of current and future earnings. Since formal and informal risk-sharing and insurance mechanisms may be ineffective as the shocks are often aggregate, adverse shocks such as these can lead to a fall in household welfare and changes in intra-household allocation of resources especially for those in the lower end of the income spectrum. As weather shocks are becoming more frequent and severe, there is a need to understand how households are affected by and respond to direct and indirect effects of the shocks in order to develop and implement policies to mitigate adverse human capital and welfare consequences.

In this paper, I investigate the effect of a frequent weather systems in the Caribbean, a hurricane, on the investment in child human capital by analysing the impact of hurricane Ivan on educational indicators among school-aged children in Jamaica using data from the 2002 and 2006 rounds of the Jamaica Survey of Living Conditions (JSLC), and data on damages to schools in the various parishes due to the hurricane. Preliminary results indicate that increased damages to schools had a negative effect on the number of days attended for girls from rural and other town areas and no effect on the probability of attending school

The paper is organised as follows: section 2 reviews relevant literature on the consequences of shocks on children's outcomes, section 3 introduces the theoretical framework, section 4 presents the background context, section 5 describes the data used in the analysis, section 6 presents the results and section 7 concludes and highlights some policy issues.

2. PREVIOUS LITERATURE

The literature on the impact of natural disaster shocks and risk on human capital such as educational attainment at the household and individual level is relatively new. However there exists substantial literature on the effect of macroeconomic crises on schooling and health outcomes which provides an idea of the effect of aggregate shocks. The limitation of these studies is that there is no element which captures the direct destruction of physical capital, infrastructure and services which often occurs with natural disasters. Notwithstanding this, there results from this literature are useful in this context. Literature on the ability of households in developing countries to smooth consumption in the face of shocks to income also provides some insight in the analysis of this issue.

From the macroeconomic shocks literature, Schady (2004) finds that for children in Peru, the prolonged macroeconomic decline of 1988-1992 lead to higher mean educational attainment for the children exposed to the shock than those who were not exposed to the crisis. The fraction of children who were both employed and attending school declined however there was no discernable effect on enrolment rates. Escobal, Saavedra & Suárez (2005) also studied economic crisis in Peru and find that the negative shock did not result in further overage among children. Fallon and Lucas (2002) reviewed the evidence of the impact of financial crises on households and report decreases in the dropout rate of primary school children and increases in the dropout rate of high school students in Mexico during the 1982 crisis. Thomas et al. find in Indonesia, a decline in enrolment rates of 8 to 13 year old but an increase in enrolment rates among 14 to 19 year olds during the 1998 financial crisis. Thus from this literature, the effect of macroeconomic shocks on child educational outcomes are ambiguous.

The effect of shocks to household income on children's outcomes is another body of literature which provides insight. Jensen (2000) finds that the presence of adverse agricultural conditions leading to variability in incomes leads to a decline in school enrolment by between one-third and one-half. Similarly, Jacoby & Skoufias (1997) find that income variability has an adverse effect on children's school enrolment with seasonal fluctuation in enrolment acting as a form of self insurance. They also find that this seasonal fluctuation in enrolment did not lead to a loss in human capital on average. Duryea, Lam & Levison (2007) studied employment shocks to households in Brazil and find significant increases the probability that a child enters the labour force, drops out of school and does not progress in school. Based on the findings in the literature, shocks to income have adverse effect on schooling.

The few papers from the natural disaster literature which specifically deals with their effect on the human capital outcomes of children include Gitter and Barham (2007), Baez & Santos (2007), Portner (2008) and Datar et al (2013). The first uses a two-stage estimation procedure to investigate the impact on school enrolment of four variables, one of which is shocks, on household decisions in rural Honduras. The shock considered is hurricane Mitch. They find that credit-constrained households were more likely to be affected by the shock and have lower educational attainment. Baez and Santos (2007) is a medium run assessment of children's vulnerability to natural disasters. They use a panel dataset and a quasi-experimental design to show that "large and aggregate shocks, such as a natural disaster, have adverse medium-run effects on children's well-being, particularly in terms of health, nutrition and labour force participation" in Nicaragua. The shock under investigation was also hurricane Mitch which hit Nicaragua in 1988. They find that hurricane Mitch had no significant effect on school enrolment however other indicators, such as the prevalence of illness and labour participation were affected. Portner (2008) used household survey data in Guatemala, combined with historical data on hurricanes, to analyse how investment in education and fertility respond to hurricane risks and shocks. He finds that hurricane shocks lead to decreases in education and higher hurricane risk lead to higher education. From these results, the impact of a natural disaster on schooling is either negligible or negative.

The most recent paper by Datar et al. (2013) focussed on child health and investment in India using data from the Indian National Family and Health Survey and an international database of natural disasters. They find that exposure to a natural disaster: in the past month increases the livelihood of acute illnesses; in the past year reduces height-for-age and weight-for-age z-scores and increases the likelihood of stunting and underweight in children under 5.

This paper contributes to the natural disaster literature by being one of the first to use a measure of direct destruction of infrastructure as the measure of exposure to the disaster. Thus it directly considers access and availability as a mechanism through which an unanticipated shock of this kind can affect human capital. Additionally it performs a microeconomic analysis of a natural disaster shock in the Caribbean, of which there is a dearth in the literature.

3. THEORETICAL FRAMEWORK

Formally, I follow Skoufias (2001) and Santos (2007) and introduce a household decision making model which illustrates the mechanisms through which a hurricane can potentially affect children's educational outcomes. For simplicity, a uni-temporal model is used in which all household decisions in early-life of children and the outcomes of these decisions in their subsequent adult life are collapsed into one time period. The model is also a unitary model in which it is assumed that the household maximizes a single welfare function without specifying any intra-household distribution of utility. Finally, households are also assumed to have full information.

The validity of these assumptions can be challenged on a number of bases. Jacoby and Skoufias (1997, 1998) find that collapsing the life cycle of the household into one period may be less acceptable for poor rural economies characterized by imperfect credit markets, liquidity constraints and limited possibilities of ensuring household consumption. Additionally, the assumption of a unitary household has been subject to criticism in the literature in which an alternative model of collective decision making within the families may more accurately reflect actual household dynamics. While these are valid critiques, this model can still be used to capture many aspects of the topic under analysis as it highlights the various costs and benefits associated with the decision to invest in the human capital of children.

3.1. HOUSEHOLD DECISION-MAKING MODEL

Parents are assumed to care about the level of household consumption (C) and the future earnings of their children (E). Thus parents are only concerned about child human capital indirectly in as much as it affects the adult earnings of the child because they expect to receive a fraction of these future earnings of their children. Thus the parents maximize the following utility function:

$$\max\ U = U(C, E) \tag{1}$$

which is assumed to have standard neo-classical properties i.e. $U^{'}(\bullet) > 0$ and $U^{''}(\bullet) > 0$.

To make the analysis simpler, the term human capital is taken to mean household investments in both education and health. As per Santos (2007), human capital has two components: S, the stock of human capital at the beginning of the period and H, the investment in human capital over the period. Children's future earnings are assumed to be a linear combination of the amount human capital $(S + H)$ and the innate ability and health endowments (γ) which is unobservable except possibly by the parents of the children. Thus

$$E = \alpha(S + H) + \beta\gamma \qquad (2)$$

Where β is the return on genetics and α is the contribution of human capital.

Investment in human capital (H) is produced using inputs of time of family members and complementary goods and services purchased in the market such as books, vaccines, etc. The reduced form of the human capital investment in the child can be represented as:

$$H = h\left(X, t_H^c, t_H^p, \theta, \gamma, \delta\right) \qquad (3)$$

The three important human capital inputs are: X – purchased goods and services e.g. books, medical care), t_H^c – the time the child spends in school, t_H^p – the time of the parents dedicated to investment in human capital of the child. Human capital investment also depends on a set of observable characteristics of the child, θ, such as age, sex, birth order; the set on unobservable characteristics of the child, γ, which include biological and genetic factors such as innate ability and health endowments which may exogenously affect H; and δ which reflect the role of parental education, community characteristics such as the availability of health facilities and schools, prices, environmental factors, distance from the market, etc. Thus the future earnings of the child can be expressed as:

$$E = \alpha\left(S + h\left(X, t_H^c, t_H^p; \theta, \gamma, \delta\right)\right) + \beta\gamma \qquad (4)$$

The first partial derivatives i.e. marginal effects of X, t_H^c and t_H^p on human capital investment are assumed to be positive. This is equivalent to assuming that the more time the child or parents dedicate to human capital investment and the more the complementary goods and services, the higher human capital embodied in the child.

At the optimum, household expenditure is equal to household resources. Expenditure consist of household consumption (excluding the goods and services purchased for human capital investment), C (assumed to be the numeraire) and the consumption of goods and services purchased for human capital investment, X. Expenditure is thus: $Np_xX + C$, where N is the number of children in the household and p_x is the vector of prices of human capital goods. The resources of the household are made up of assets (A) and income. Income can be from four sources: non-labour income of the household (Y_{nl}), labour income of the parents $(W_p(T - Nt_H^p))$, labour income of children today $(W_c(T - t_H^c)N)$ this incorporates the possibility that the children can contribute to household income while not engaged in human capital accumulation), and a fraction ω of the earnings of adult children $(\omega\ N_A E)$. The labour income of parents is equal to their wage W_p times the number of time units they dedicate to work (the difference between total time endowment T and the time dedicated to human capital investment in their children). Similarly the labour income of each child s equal to his/her wage W_c times the number of time units dedicated to work. Thus in this model there is the possibility of children to be enrolled in school as well as working. The budget constraint of the household is thus:

$$Np_x X + C = Y_{nl} + W_p\left(T - Nt_H^p\right) + W_c(T - t_H^c)N + \omega N_A E + A \tag{5}$$

The household thus maximises (5) subject to the restraints (3), (4) and (5) by choosing the levels of household consumption (C), the consumption of complementary goods and services and the time allocation of parents and children to human capital accumulation (t_H^c, t_H^p). The first order conditions of the maximisation problem are:

$$MRS_{CE} = \frac{U_E}{U_C} = N\left(\frac{W_c}{\alpha H_{t_H^c}} - \omega\right) = MC_{t_H^c} \tag{6}$$

$$MRS_{CE} = \frac{U_E}{U_C} = N\left(\frac{W_p}{\alpha H_{t_H^p}} - \omega\right) = MC_{t_H^p} \tag{7}$$

$$MRS_{CE} = \frac{U_E}{U_C} = N\left(\frac{P_x}{\alpha H_x} - \omega\right) = MC_x \tag{8}$$

From expressions (6), (7), and (8) it can be seen that at the optimum the marginal rate of substitution between household consumption and the adult children's earnings (denoted by the ratio of the partial derivatives of the utility function with respect to E and C) is equal to the marginal cost or "shadow price" of investing the human capital of the child. Additionally, combining the three first order conditions of these implies that households maximizes utility by allocating child time (t_H^c), parental time (t_H^p), and complementary goods and services (X) such that the marginal costs associated with each activity and resource are the same i.e., $MC_{t_H^c} = MC_{t_H^p} = MC_x$

Expression (6) implies that the marginal cost of children's time in human capital accumulation depends positively on the wage rate of children, W_c , which can be thought of as opportunity cost of time in school, and depends negatively on the marginal increases in adult earnings due to a unit increase in time in school. Additionally, ceteris paribus, the marginal cost of investing in child human capital is higher the larger the number of children in the household as more children. Similarly, in expression (7) the marginal cost of the time the parents allocates to human capital accumulation depends on the wage rate of the parents and the marginal productivity of parents' time in the accumulation of human capital. When combines, expressions (6) and (7) imply that at the optimum, households will allocate the time children and parents spend in human capital production such that the marginal costs of the two activities are equal.

Non-labour income Y_{nl} does not enter directly into expressions (6) – (8) and so changes in it leaves the shadow prices of the resources unchanged. Thus increases in Y_{nl} result in "pure income effects" that increase human capital and consumption, provided that E and C are "normal" goods. On the other hand, changes in any of the factors that affect the marginal cost of time and goods used in producing human capital can cause substitutions between the resources used in human capital production as the household minimizes its production costs and maximizes its welfare by using more of the input whose shadow price decreased and less of the input whose shadow price increased.

3.2. DISASTERS AND HUMAN CAPITAL FORMATION

Natural disasters can adversely affect household income, household assets as well as the health and well-being of household members. On a macro scale, there can also be effects on the country's infrastructure and economic environment. In the short to medium term households' investment in child education and more widely human capital accumulation can be impacted through three main channels. Firstly, there are direct effects such as damages sustained to schools and health services and infrastructure, loss of household assets and fatalities and injuries to household members. Also there can be direct mental and psychological effects on individuals which can affect ability to process information and learn.

Secondly there is the indirect impact to household income which can be positive or negative. Income can be adversely affected due to loss of income generating assets such as crops, livestock, etc, loss of jobs, injuries that can prevent individuals from working or reduce their working hours. On the other hand, there may be increases in income due to jobs created during the reconstructive efforts as well as inflows of remittances and aid from abroad. Finally, there are downstream effects due to the initial slowdown in the economy which will affect most households.

Each of the channels through which a natural disaster can impact household welfare has different implications for the optimal allocation decision of the household. In the model, damages to educational, health and other complementary infrastructure and services, ceteris paribus, lead to the household investing less in children's health and schooling as the marginal cost of the goods and services associated with human capital production increases.

Destruction of the productive assets of the household also lead to a reduction in investment in human capital as it constitutes a decrease in the permanent income of the household. Injuries that may incapacitate household members, loss of agricultural produce, jobs, etc. leads to a fall in income which can further reduce household income and tighten the budget constraint. This drop in income may or may not be offset by increases in employment due to the reconstruction efforts and inflows of remittances from abroad.

The initial slowdown of the economy generally reduces labour demand and wages. This decrease in wages causes an income and substitution effect in which investment in human capital should increase because the opportunity cost of human capital (wages) is now lower. As the income effect may go in the opposite direction, the net change is ambiguous.

In summary, the potential reallocation of household resources as a result of a shock such as a hurricane can reduce the resources allocated to investments in human capital. Since some households may be credit constrained and cannot obtain loans in order to invest in basic education, the need to lower consumption in the face of fluctuating income may lead them to withdraw their children from school. Additionally, as a risk-reduction mechanism, households can use children's work to make up for the shortfall in adult income. This means that the child has less time available to dedicate to studies and hence development of human capital. This can affect the pace of the child's educational progress if he/she has to repeat grades and/or withdraw from school for a period of time which can as a consequence reduce future productivity and earnings. The availability and accessibility of school facilities after a disaster can also play an important role in households' investment in child human capital. The cost of sending a child to school increases and if there is substantial damage, parents may not send their children to school if they think school quality has decreased in the aftermath of a disaster making it more worthwhile to keep the children at home.

4. BACKGROUND

4.1. JAMAICAN CONTEXT

Jamaica is a small island developing state located in the Caribbean about 90 miles south of Cuba, and 120 miles west of Haiti. It is the third largest island in the Caribbean with most of its major towns and cities situated along the coast. Kingston, the capital of the island, is also the largest city with over 20 percent of the population living there. The island is divided into 14 parishes, which are grouped into three historical counties, Cornwall in the west, Surrey in the East and Middlesex in the Middle.

Jamaica also lies in the Atlantic hurricane belt with the hurricane season coinciding with the wet season from June to November. Due to this, Jamaica has been exposed to a number of tropical storms and hurricanes in the past. Two powerful hurricanes which have directly hit the island were hurricane Charlie in 1951 and hurricane Gilbert in 1988 both of which caused fatalities and significant destruction.

4.2. HURRICANE IVAN

Hurricane Ivan was category 4 hurricane when it reached the vicinity of Jamaica in September 2004. The effects of the hurricane on Jamaica had been felt from September 9 with thunder showers and thunderstorms in the east and southwest of the country (See Figure 1 for the Track Chart of Hurricane Ivan). The hurricane passed closest to Jamaica on September 11 with sustained winds of 180 kilometres per hour. Gusts as high as 340 km/h were recorded in certain parts of the island, storm waves and sea surges were reported along the eastern and southern coast line and rainfall exceeded the average depth by over 4 times in parishes such as Clarendon, St. Catherine and Kingston/St. Andrew. [2]

The total damages sustained by hurricane Ivan amounted to approximately US$ 595 million. Of this, 63 percent refers to direct losses from damages to physical assets such as schools, health centres, utilities, etc, and the other 37 percent refers to indirect losses due to changes in economic flows over the medium term. This total amount is equivalent to 8 percent of 2003 GDP. The private sector sustained the major portion of the damage (74 percent) while the public sector had the remaining impact (26 percent).[1]

---

[2] Assessment of the Socioeconomic and Environmental Impact of Hurricane Ivan on Jamaica; ECLAC, UNDP and the Planning Institute of Jamaica (PIOJ)

Housing was the single most affected sector with 14 percent of households reporting damage to properties. In the social sectors, damage to the school sector was also widespread with 33 percent of schools suffering damages. Eight of the 14 parishes had 30 percent or more of their schools damaged by the hurricane. Of the schools that were damaged, 90 percent of them required repair. The health sector also suffered acute damage with 36 percent of the health centres being damaged. The productive sectors also sustained heavy damages with agriculture and livestock, food processing, mining, commerce and tourism, suffering significant losses. Infrastructure was also affected but not as severely as the social and productive sectors. To summarise the impact of hurricane Ivan, the Assessment of the Socioeconomic and Environmental Impact of Hurricane Ivan on Jamaica conducted by ECLAC, UNDP and the Planning Institute of Jamaica states:

> "It is possible to assert that the disaster caused by hurricane Ivan in Jamaica can be described, in broad terms, as one that destroyed or damaged assets of housing, transport infrastructure, the environment and some permanent agricultural plantations, while at the same time imposing a decline in future agriculture and livestock and food processing production and in the tourism industry, as well as bringing about decreased revenues and increased operational costs of utilities in the electricity, water supply, telecommunications and transport sectors".

5. DATA

5.1. JAMAICA SURVEY OF LIVING CONDITIONS

The source of the individual-level data used in this paper is 2002 and 2006 rounds of the Jamaican Survey of Living Conditions (JSLC). The JSLC is a nationally representative survey modelled after the Living Standards Measurement Surveys (LSMS) of the World Bank. It is conducted annually by the Statistical Institute of Jamaica (SIOJ) and the Planning Institute of Jamaica (PIOJ) and collects information on health, education, expenditures, housing and household characteristics among other things. Although the survey does not include a community questionnaire, information on distance to and availability of certain services and infrastructure is collected in relevant modules.

The questionnaire and coverage of the two survey years are comparable. The education modules contain questions on the educational status of each household member over the age of three years such as the type of school attended, the grade presently in, etc. Two educational indicators of interest: school enrolment and the number of days attended during the reference period were constructed from the data.

From the model introduced earlier, household investment in human capital accumulation is a function of individual characteristics, household demographic characteristics, and the services and infrastructure available. As such, data from the household roster, the expenses modules and housing module were used to construct additional variables necessary for the analysis. The main individual-level variables used are: age, sex and a dummy variable for whether the child is the offspring of household head. The household-level variables are: log of per capita annual household expenditure, dummy variable for living below the poverty line, dummy variable for ownership of dwelling, household size, the number of women in the household and the number of children in the household. As there was no community level questionnaire, the variables used to proxy this are dummies for whether the household lives in Kingston Metropolitan Area, rural areas or other town areas.

The sample consists of 13 to 16 year olds from the households interviewed for the JSLC. This age group was chosen so that the potential of overlap between the two years would be minimised since the individuals in the age range 13 to 16 in 2002 would not be in the 2006 sample of 13 to 16 year olds. This removes one source of potential bias in the results. A total of 2,580 individuals comprise the main sample used for the school enrolment regression and 2298 individuals for days attended in reference period regression.

5.1.1. SAMPLE AND DESCRIPTIVE STATISTICS

The mean characteristics of the full sample in 2002 and 2006 are shown in Table 1. Additionally, the sample is subdivided by area: Kingston Metropolitan Area (KMA), Other Towns and rural; and by gender. The average age of individuals in the 2002 sample is 14.48 with slightly more than half of them being males. In 2006 the average age increased slightly to 14.55 years but with slightly less than half of the sample being male. The average age is similar for males and females in both years. In 2002, 63 percent of the sample resided in rural areas, 19 percent resided in other town areas while 18 percent resided in the KMA. This distribution changed in 2006 with individuals residing in KMA rising to 29 percent, other town residents rising to 21 percent and rural residents falling to 50 percent and. Log of household per capita expenditure increased in 2006 to 11.49 from 10.86 in 2002. Households in the KMA and other towns had higher household expenditure that those in rural areas in both years. Approximately two-thirds of households owned a dwelling in 2002 with more rural residents owning a house than KMA and other town residents. This proportion fell in 2006 to 63.1 percent with the same trend for rural versus other town and KMA residents.

Household size averaged 5.9 persons in 2002 and 5.5 persons in 2006. Rural households were bigger than those in other towns and KMA. In 2002, boys and girls came from households of similar size (5.94 and 5.91) whereas in 2006, girls came from bigger households of an average of 5.58 persons than boys who came from households of average size 5.36 persons. 66 percent of individuals in the sample in 2002 were the offspring on the household head as compared to 71 percent in 2006.

The proportion of individuals in the sample attending school was similar with 91 percent attending in 2002 and 92 percent attending in 2006. The average number of days attended in 2002 is 18.13 days, lower than the average of 18.58 in 2006. In all areas except rural, the proportion attending school increased between 2002 and 2006 and for all areas, the number of days attended increased between 2002 and 2006. In both years a higher proportion of females were attending school, with 93 percent of girls attending school versus 89 percent of boys in 2002 and 93 percent of girls versus 90 percent of boys in 2006. Additionally the proportion attending school increased between 2002 and 2006 for both boys and girls. There is a similar gap and trend for the number of days attended.

5.2. HURRICANE IVAN EXPOSURE

In the absence of individual-level or household-level information on exposure to the hurricane, exposure is assessed at the level of the household's parish of residence.[3] A parish level variable provides a measure of the likelihood that the individual or household was affected by the hurricane. The specific measure used is the percentage of schools requiring repair after the hurricane (see Table 2). The percentage of schools requiring repair ranges from 12.6% in St. Elizabeth to 75% in Hanover. The average percentage requiring repair is 32.2% and the median is 29.6%. The figures were obtained from the Assessment of The Socioeconomic and Environmental Impact of Hurricane Ivan on Jamaica (2004) undertaken by the Economic Commission for Latin America and the Caribbean (ECLAC), the United Nations Development

[3] Jamaica is divided into 14 administrative regions or parishes.

Programme (UNDP) and the PIOJ. This type of assessment is conducted after each natural disaster and serves to provide to the Ministry of Finance for planning the reconstruction strategy and to contribute to identifying the financial needs and implication for the country. The assessment was made following the standard ECLAC methodology for the socioeconomic and environmental assessment of disasters.

5.2.1. CORRELATIONS

Table 3 shows the change in the variables of interest by parish from 2002 to 2006 and the correlation between these changes at the parish level with the measure of exposure to the hurricane. As is shown in the table, at the parish level there is a positive correlation between the average percentage change in the proportion of individuals attending school and the percentage of schools requiring repair, and a negative correlation between the change in the average number of days attended and the percentage of schools requiring repair. The correlations are small however the signs indicate that parishes with higher damages resulting from hurricane Ivan had higher percentage change in the proportion of individuals attending school and lower percentage change in the average number of days attended.

6. EMPIRICAL ANALYSIS

6.1. SPECIFICATION

The empirical strategy considers hurricane Ivan as a natural experiment equivalent to a random unanticipated shock and exploits variation in the intensity of its impact across parishes and across years using a difference-in-differences approach with variation in treatment intensity[4]. A reduced form is estimated in which the schooling outcome is a function of household, individual and demographic characteristics.

$$OUT_{ipt} = \alpha + \beta_1 Exposure_p + \beta_2\, Year_t + \beta_3\, Exposure_p{*}Year_t + \mathrm{X}_{ipt}\,\gamma + \varepsilon_{ipt} \qquad (1)$$

Where *OUT* is school enrolment or number of days attended, $Exposure_p$ is the number of schools requiring repair at the parish level, *Year* is a year dummy, $Exposure_p{*}Year_t$ is their interaction term and the variable of interest, X is a vector of individual characteristics, household

[4] See Duflo (2001) for an example of Difference-in-Differences with variation in treatment intensity.

demographics and services and infrastructure available and is the error term. In (1) β_3 can be interpreted as the effect of differential exposure in 2006 on the school outcome. The models are run using a pooled sample from the 2002 and 2006 datasets on the full sample of 13 – 16 years old and various sub-samples.

The impact on school enrolment is analyzed with the Probit model because of the binary choice nature of the dependent variable and that on the number of days attended is analyzed using the Poisson model because of the count nature of the dependent variable. [5][6]

6.2. RESULTS

6.2.1. SCHOOL ENROLMENT

The results for the school enrolment regressions are shown in Table 4. The full sample results are shown in column 1 and subsamples by gender and area are shown in columns 2 - 6. The numbers in parenthesis are clustered robust standard errors, clustered at the enumeration district level.[7] As is seen in the column (2) of the table, the marginal effect of the exposure-year interaction term is 0.0124 however it is statistically insignificant. The direct year effect is negative and insignificant and the direct exposure effect is also negative but is significant at the 5 percent level. This indicates that children in areas with higher exposure to hurricane Ivan were less likely to be enrolled in school regardless of the year. This could be because areas with lower enrolment rates in 2002 were in areas more damaged by the hurricane. As expected, age is negative and significant and log of per capita household expenditure is positive and significant indicating that older children were less likely to be enrolled in school and children from households with higher expenditures were more likely to be enrolled in school. The dummy for whether the family owns a dwelling is also positive but is insignificant. The dummy for gender is also a significant variable and is negative indicating that males were less likely to be enrolled in school. When the sample is separated by gender in columns 2 and 3, the coefficient on the exposure-year interaction term is positive for boys and negative for girls. This suggests that the hurricane increased the probability of being enrolled in school for boys and decreased the probability for girls, however both coefficients were insignificant. Age and household expenditure are significant and in the expected direction for both boys and girls. For boys, the

[5] Logit and Linear Probability Models regressions were also used and results do not differ significantly.
[6] The results are robust to other model specifications such as negative binomial and OLS.

more females in the household the higher the probability of being enrolled in school while for girls being the offspring of the household head significantly increases the probability of being enrolled in school. The direct effect of exposure is negative and insignificant for both boys and girls and the direct year effect is negative for both but significant only for boys. None of the area variables are significant. In unreported results, I also added mother's years of schooling as an additional control as this has been found in the literature to be significant factor. This substantially reduced the sample size as schooling information was not given for a large proportion of the respondents. The full sample coefficient on the interaction term became negative but was still insignificant. The other coefficients were similar in size and significance to the results in column 1. The coefficient on mothers schooling was positive but insignificant.

Columns 4, 5 and 6 show the results by area. The interaction term is insignificant for all three areas and is positive for KMA and rural areas and negative for other town areas suggesting that the impact of the hurricane on school enrolment did not differ by area. All direct year effects are negative and is significant only for rural areas suggesting that school enrolment was lower in 2006 than in 2002 for rural areas. The direct exposure effect is negative and significant for both KMA and rural areas and positive and insignificant for other town areas. This indicates that individuals in both KMA and rural areas who live in parishes that had higher exposure to the hurricane are less likely to be enrolled school. Again age and log of household expenditure are significant and of the expected signs. In the KMA, boys were significantly less likely to be enrolled in school but not in other town or rural areas. In other town areas, the number of children in the household is positive and significant suggesting that the more children in the household the higher the probability of being enrolled in school. This is somewhat counter intuitive as more children means that resources dedicated to school expenditure is shared among more individuals. Finally in rural areas, offspring of the household head were significantly more likely to be enrolled in school suggesting a bias towards one's own children.

6.2.2. NUMBER OF DAYS ATTENDED SCHOOL

Table 5 reports the results of Poisson regressions with number of days attended in the reference period as the dependent variable. The full sample results are shown in column 1 and subsamples by area and gender are shown in columns 2 to 6. In the full sample the coefficient on the exposure-year interaction term is negative and insignificant. The direct year effect is positive and significant indicating that the average number of days attended increased between 2002 and 2006. The direct year effect is also positive but insignificant. Log of per capita household expenditure is positive and significantly related to the number of days attended indicating that children from richer households attend more days of school on average. The other indicator of household wealth, the dummy variable for house ownership is also positive and significant at the 10 percent level. It indicates that children from households that own a dwelling attend school for more days on average. The other significant variable is the number of women in the household. It is positively related to the number of days attended suggesting that households with more women sent their children to school more often. The other variables were insignificant.

Columns 2 and 3 show the results disaggregated by gender. As with school enrolment, the coefficient on the exposure-year interaction is positive for boys and negative for girls, however the coefficients are insignificant. The direct year effect is positive for both boys and girls but significant only for girls. This suggests that for girls in 2006 attended more days of school on average than girls in 2002. The direct exposure effect is negative for boys and positive for girls but insignificant. All the other variables are insignificant.

Columns 4, 5 and 6 show the result by area. The interaction coefficient is negative for all three areas and is also significant for other town areas. The direct year effect is positive for all three areas and is significant for both other town and rural areas. This indicates that in those two areas individuals attended more days of school on average in 2006 than in 2002. The coefficient on the direct exposure variable is negative for KMA but insignificant and positive and significant for other town and rural areas suggesting that in other town and rural areas, children with higher exposure to the hurricane Ivan were attended more days of school on average regardless of the year. Log of per capita expenditure is positive and significant in all areas suggesting that richer households send their children to school for more days on average in all areas. In rural areas the number of women in the household is positively and significantly related to the number of days attended suggesting that in rural area the presence of more women in the household increases the number of days children are sent to school. This could be because women in rural areas invest more in human capital of the children.

To further explore the impact by area, regressions were run on area subsamples by gender. The results are shown in Table 6. For rural and other town girls, there is a negative and significant coefficient on the exposure-year term. This means that girls from rural and other town areas in 2006 in more affected parishes on average attended less days of school than those girls in 2002. The coefficient is not significant for the other subsample and is negative for other town and KMA boys and positive for rural boys and KMA girls. The pure year and exposure effects are positive and significant for other town and rural girls suggesting that for girls from these area, the average number of days attended was more in 2006 than in 2002 and was more in areas with higher exposure. The year coefficient is also positive and significant for boys from other town areas. Log of per capita household expenditure is positive and significant for all subsample except boys from the KMA which is insignificant indicating that richer household in had children who attended school for more days on average. The dummy for dwelling ownership is also significant for girls from the KMA. The other significant variable of interest is the number of women in the household which is also positive and significant for rural girls indicating that in rural areas having more women in the household increase the number of days attended for girls but not for boys. This suggests that women in rural areas may be more invested in making sure that girls attend school on a regular basis.

6.2.3. MECHANISMS

The main result of the above analysis is that there is a negative effect of exposure to hurricane Ivan on the number of days attended during the reference period for girls from rural and other town areas. Overall boys are not affected and individuals from the KMA are not affected. This is an interesting result in the sense that most of the literature on education outcomes by gender in Jamaica indicates that boys have lower enrolment and higher dropout rates than girls. One potential reason for this result is that because of this differential, girls are the ones more likely to be affected by exposure to the hurricane if boys are already not attending school more frequently. It is possibly that only girls from outside the KMA are most affected because it is more difficult to access schools outside of KMA and so in the medium-term aftermath of the hurricane, the these girls are the ones who begin to miss days if they are needed in the household whilst the boys remain in school.

This analysis, although using damages to education infrastructure as the measure of exposure, does not determine the specific channel through which the negative effect on days attended school for rural and other town girls. One potential channel is that the hurricane reduced accessibility of education institutions and another is that the hurricane reduced household income leading to reduction in investment in human capital for girls. With the available data, this cannot be empirically identified however there is some suggestive evidence. If it is the income channel then, one would expect that expenditure on education expenses would be affected similarly by the measure of exposure. Thus I run a regression with the log of education expenses as the dependent variable and the *Exposure*Year* interaction from equation (1) as the main variable of interest. In unreported results, the interaction term is negative and significant at the 10 percent level for rural girls and negative and insignificant for other town girls suggesting that at least for rural girl, the income channel may partly be the mechanism responsible for the result.

6.2.4. ROBUSTNESS CHECKS

The above result for rural girls is robust to a variety of sensitivity analyses (Table 7). First, in this difference-in-differences specification, the exposure variable is continuous and effects are identified by differential intensity of exposure. As a check on the specification, I employ a more standard difference-in-differences framework in which parishes are separated into "high exposure" and "low exposure" parishes. High exposure is defined as having a percentage of school requiring repair larger than the median value. A reduced form was then estimated in which the schooling outcome is a function of household, individual and demographic characteristics.

$$OUT_{ipt} = \alpha + \beta_1 High_p + \beta_2\ Year_t + \beta_3\ High_p \times Year_t + \mathrm{X}_{ipt}\ \gamma + \varepsilon_{ipt} \qquad (2)$$

Where *OUT* is school enrolment or number of days attended, $High_p$ is a dummy for whether a high exposure parish, *Year* is a year dummy, $Exposure_p \times Year_t$ is their interaction term and the variable of interest, X is a vector of individual characteristics, household demographics and services and infrastructure available and is the error term. In (2) β_3 can be interpreted as the effect of having high exposure in 2006 on the school outcome. The substantive results do not change, and the main result of negative impact on the number of days attended for girls in rural still hold however the coefficient on the interaction term for other term girls is now positive and insignificant (Table 7).

The results are also robust to expanding the age range of the sample from 13 to 16 to 7 to 16. The main results still hold though the point estimates are smaller (Table 7), the number of days attended in the reference period is still significantly less for girls with higher exposure in rural and other town areas. Another check was to analyze the effect for the specific cohorts. Thus instead of comparing 13 to 16 year olds in 2002 with 13 to 16 years olds in 2006, I compare 9 to 12 years olds in 2002 with 13 to 16 years olds in 2006. This 2002 cohort would have been directly affected by the hurricane and would be 13 to 16 in 2006, hence the comparison. So although the data doesn't track individuals as is not longitudinal, it is possible look at a comparable group 4 years later. The main result for other town girls is still negative but is not insignificant, but for rural girls is still negative and significant. This also holds if the 2002 cohort is 8 to 11 years old.

6.2.5. OTHER CONSIDERATIONS

There were a number of factors which can have an effect on the analysis in this study and which may have affected the results obtained. First, while the dataset used contained a wide range of data, there were items which were not collected that could have allowed for more detailed analysis. There was a lack of household and individual income data which meant that household expenditure was used as a proxy for it. Since expenditure on schooling is a component of household expenditure and educational expenditure may influence whether or not a child is sent to school, there could be a bi-causal relationship between the two. To correct for this, education expenditure is subtracted from total expenditure and the log per capita of this is used as a regressor instead of log of total per capita household expenditure. The results are very similar, with the size of interaction term for other town girls increasing and the interaction term remaining significant for both rural and other town girls.

Another issue is that the variable for exposure to the hurricanes is computed at the parish level which assumes that children attend school in the parish in which they reside which may not always be the case. One reason why this may not be a big problem is because the survey was conducted during the school term and so for students who may have been boarding in another parish to attend school there, they would be captured in the parish in which they attended school. Notwithstanding this, to control for this, the regressions were limited to individuals who attended school within 10 miles of their homes. The main results are again robust to this suggesting that the effect is real and not due to this potential bias.

Also important is the issue of migration. If the household has moved due to the hurricane to another parish, then their exposure to the hurricane will not be accurately measured. These measurement issues in the independent variable may lead to a downward bias of the estimates.

This cannot be checked as the dataset has no questions on migration or migration history, however to the extent that migration may be an issue, then the estimates presented reflect lower bounds to the actual effect.

7. CONCLUSION AND POLICY ISSUES

The literature suggests that households in developing countries including those in the Caribbean are unable to perfectly smooth consumption across time and space because risk-sharing and risk-coping strategies are incomplete and largely informal. Understanding the effect of natural disasters on household welfare is thus very important, so that households are not left severely negatively impacted by their occurrence. The literature on the impact of natural disaster on household and individual outcomes and in particular investment in human capital of children is relatively small and this study aims to add to this body of literature.

The results indicate that in the short to medium term, hurricane Ivan had a negative effect on the number of days individuals attended school for girls who are not in the Kingston Metropolitan Area while the probability of attending school was unaffected. This suggests that households in rural and other town areas reallocate resources and reduce the number of days their girl children are sent to school after a shock. Thus, one clear policy directive is for the disruption of educational facilities after a disaster be minimised. Rebuilding efforts need to be undertaken as soon as possible. Additionally, policies that target rural and other town households need to be considered. One possibility is providing conditional transfers to the households that are most affected. This would provide additional income which can offset the increase in the costs involved in sending the child to school consistently.

REFERENCES

Alderman, H., P.-A. Chiappori, et al. (1995). "Unitary versus Collective Models of the Household: Is It Time to Shift the Burden of Proof?" The World Bank Research Observer **10**(1): 1-19.

Adkins, L. C. and R. C. Hill (2008). Using Stata for principles of econometrics. Hoboken, NJ :, Wiley

Anderson, M. B. (1990). Analyzing the costs and benefits of natural disaster responses in the context of development, Washington, D.C., World Bank Environmental Department

Auffret, P. (2003). "High Consumption Volatility: The Impact of Natural Disasters?" World Bank Policy Research Working Paper 2962

Binder, M. (1999). "Community effects and desired schooling of parents and children in Mexico." Economics of Education Review **18**(3): 311-325

Charveriat, C. (2000). "Natural disasters in Latin America and the Caribbean: An overview of risk." Working Paper 434, Inter-American Development Bank, Washington, D.C.

Clarke, G. and S. Wallsten (2003), "Do Remittances Act Like Insurance? Evidence from a Natural Disaster in Jamaica", Development Research Group, World Bank, Washington D.C.

de la Fuente, A. and R. Fuentes (2007). The Impact of Natural Disasters on Children Morbidity in Rural Mexico. Human Development Report 2007/2008, Occasional Paper. H. D. R. Office.

Datar, A., et. al. "The impact of natural disasters on child health and investments in rural India" Social Science and Medicine **76**: 83-91.

Deaton, A. (1997). The analysis of household surveys : a microeconometric approach to development policy. Baltimore, MD :, Published for the World Bank [by] Johns Hopkins University Press.

Dercon, S. (2002). "Income Risks, Coping Strategies and Safety Nets." The World Bank Research Observer **17**(2): 141-166

Duflo, E., (2001). "Schooling and Labor Market Consequences of School Construction in Indonesia: Evidence from an Unusual Policy Experiment." American Economic Review **91**(4): 795-813

Duryea, S., D. Lam, et al. (2007). "Effects of economic shocks on children's employment and schooling in Brazil." Journal of Development Economics **84**(1): 188-214.

ECLAC, UNDP, et al. (2004)."Impact of Hurricane Ivan on Jamaica: Socioeconomic and Environmental Assessment."

Escobal, J., J. Saavedra, et al. (2005) Economic Shocks and Changes in Attendance Levels and Education Expenditure in Peru. Working Paper no. 13, Young Lives.

Fallon, P. and R. Lucas (2002). The Impact of Financial Crises on Labor Markets, Household Incomes, and Poverty: A Review of Evidence. The World Bank Research Observer **17**(1), 21 – 45

Gitter, S. R. and B. L. Barham (2007). "Credit, Natural Disasters, Coffee, and Educational Attainment in Rural Honduras." World Development **35**(3): 498-511.

Handa, S. (1994). "Gender, headship and intrahousehold resource allocation." World Development **22**(10): 1535-1547.

Handa, S. (1996). "The determinants of teenage schooling in Jamaica: Rich vs. poor, females vs. males." Journal of Development Studies **32**(4): 554-580

Hutton, D. (2004). "Psychosocial effects of a natural disaster: a post-flood assessment in the red river valley." Environments **32**(2): 27(17).

Jacoby, H. G. and E. Skoufias (1997). "Risk, Financial Markets, and Human Capital in a Developing Country." Review of Economic Studies **64**(3): 311-335.

Jacoby, H. G. and E. Skoufias (1998). "Testing theories of consumption behavior using information on aggregate shocks: Income seasonality and rainfall in rural India." American Journal of Agricultural Economics **80**(1): 1-14.

Jensen, R. (2000). "Agricultural volatility and investments in children." American Economic Review **90**(2): 399-404.

Long, J. S. (1997). Regression models for categorical and limited dependent variables. Thousand Oaks :, Sage Publications.

Otero, R. and R. Marti (1995). "The impacts of natural disasters on developing economies: Implications for the international development and disaster community." Disaster Prevention for Sustainable Development: Economic and Policy Issues.

Paxson, C. and N. Schady (2005). "Child health and economic crisis in Peru." World Bank Economic Review **19**(2): 203-223.

Portner, C. C. (2008). Gone With the Wind? Hurricane Risk, Fertility and Education, Department of Economics, University of Washington.

Santos, I. and J. E. Baez (2007). "Children's Vulnerability to Weather Shocks: A Natural Disaster as a Natural Experiment". doctoral dissertation, Kennedy School of Government, Harvard University.

Schady, N. R. (2004). "Do macroeconomic crises always slow human capital accumulation?" World Bank Economic Review **18**(2): 131-154.

Skidmore, M. and H. Toya (2002). "Do Natural Disasters Promote Long-Run Growth?" Economic Inquiry **40**(4): 664-687.

Skidmore, M. and H. Toya (2005). Economic Development and the Impacts of Natural Disasters, UW-Whitewater, Department of Economics.

Skoufias, E. (2001). PROGRESA and Its Impacts of the Welfare of Rural Households in Mexico. Research Report **139**, International Food Policy Research Institute, Washington, D.C.

UNDP (2004). Reducing Disaster Risk: A Challenge for Development, Bureau for Crisis Prevention and Recovery, United Nations Development Programme

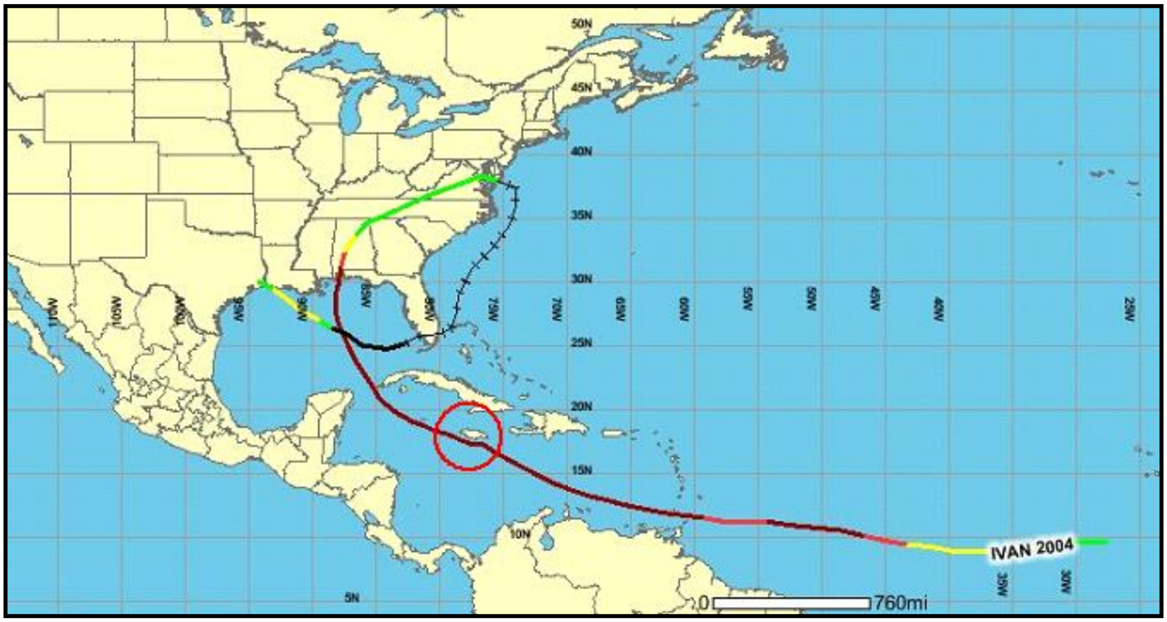
UNESCO, International Association of Universities, Higher Education Systems, Jamaica Education System, www.unesco.org/iau/online**database**s/systems_data/jm.rtf

UNICEF, Jamaica Statistics, http://www.unicef.org/infobycountry/jamaica_statistics.html

UNICEF, Jamaica, Monitoring the Situation of Women and Children, Multiple Indicator Cluster Survey 2005

Wooldridge, J. M. (2002). Econometric analysis of cross section and panel data. Cambridge, Mass. ; London :, MIT Press.

Figure 1: Hurricane Ivan Track Chart



Source: National Oceanic and Atmospheric Administration (NOAA) Coastal Service Centre, Historical Hurricane Tracks

Table 1: Sample Means and Proportions

	Total Sample		KMA		Other Towns		Rural		Males		Females	
Year	2002	2006	2002	2006	2002	2006	2002	2006	2002	2006	2002	2006
In School	0.907	0.918	0.935	0.949	0.90	0.921	0.899	0.899	0.887	0.901	0.928	0.934
	(.290)	(.275)	(0.247)	(0.221)	(0.291)	(0.271)	(0.301)	(0.301)	(0.317)	(0.299)	(0.259)	(0.248)
Number of Days	18.13	18.58	18.40	17.96	18.31	19.09	18.00	18.74	17.94	18.35	18.31	18.80
	(3.99)	(3.20)	(4.09)	(4.39)	(3.78)	(2.54)	(4.02)	(2.49)	(4.07)	(3.50)	(3.91)	(2.88)
Age	14.48	14.55	14.41	14.52	14.47	14.34	14.50	14.65	14.47	14.58	14.48	14.52
	(1.14)	(1.07)	(1.11)	(1.09)	(1.15)	(1.13)	(1.14)	(1.04)	(1.13)	(1.07)	(1.14)	(1.08)
Male	0.506	0.496	0.475	0.485	0.524	0.475	0.510	0.512				
	(.500)	(.500)	(0.500)	(0.501)	(0.500)	(0.501)	(0.500)	(0.501)				
Offspring of household head	0.657	0.709	0.736	0.791	0.675	0.650	0.630	0.686	0.660	0.707	0.655	0.711
	(.475)	(.455)	(0.441)	(0.408)	(0.469)	(0.479)	(0.483)	(0.465)	(0.474)	(0.456)	(0.476)	(0.454)
KMA	0.180	0.286							0.169	0.279	0.192	0.292
	(.385)	(.452)							(0.375)	(0.450)	(0.394)	(0.456)
Other town	0.186	0.211							0.193	0.201	0.179	0.220
	(.389)	(.408)							(0.395)	(0.402)	(0.384)	(0.415)
Rural	0.633	0.504							0.637	0.519	0.629	0.488
	(.482)	(.500)							(0.481)	(0.500)	(0.483)	(0.501)
Log (per capita household	10.86	11.49	11.13	11.67	10.92	11.62	10.76	11.33	10.82	11.49	10.89	11.49
expenditure)	(.644)	(.603)	(0.695)	(0.582)	(0.641)	(0.520)	(0.605)	(0.607)	(0.658)	(0.584)	(0.630)	(0.623)
Household size	5.92	5.47	5.5	5.32	5.74	5.34	6.10	5.61	5.94	5.36	5.91	5.58
	(2.73)	(2.43)	(2.63)	(2.50)	(2.53)	(2.16)	(2.80)	(2.49)	(2.81)	(2.20)	(2.65)	(2.64)
Household owns dwelling	0.670	0.631	0.455	0.503	0.583	0.650	0.756	0.696	0.690	0.647	0.649	0.615
	(.470)	(.483)	(0.499)	(0.502)	(0.484)	(0.479)	(0.429)	(0.461)	(0.463)	(0.479)	(0.476)	(0.487)
Number of Women	3.20	3.15	3.08	3.07	3.09	3.18	3.26	3.18	2.66	2.62	3.75	3.68
	(1.86)	(1.82)	(1.81)	(1.84)	(1.74)	(1.62)	(1.90)	(1.90)	(1.84)	(1.69)	(1.71)	(1.81)
Number of Children	2.56	2.46	2.26	2.37	2.50	2.32	2.66	2.57	2.52	2.43	2.60	2.49
	(1.50)	(1.45)	(1.28)	(1.49)	(1.30)	(1.20)	(1.44)	(1.34)	(1.41)	(1.32)	(1.39)	(1.41)

Table 2: Parish-level exposure to hurricane

Parish	% of Schools Requiring Repair
Kingston	0.1697
St. Andrew	0.1697
St. Thomas	0.2708
Portland	0.4340
St. Mary	0.2394
St. Ann	0.3457
Trelawney	0.2368
St. James	0.4286
Hanover	0.7500
Westmoreland	0.3846
St. Elizabeth	0.1264
Manchester	0.3562
Clarendon	0.3143
St. Catherine	0.2787
Mean	0.3217
Median	0.28

Table 3: Parish-level correlations of variables of interest and exposure to hurricane

PARISH	Enrolment			Days Attended			% Requiring Repair
	2002	2006	% Δ	2002	2006	% Δ	
Kingston	0.970	0.947	-2.33	18.74	18.33	-2.15	16.97
St. Andrew	0.916	0.940	2.60	17.91	17.80	-0.66	16.97
St. Thomas	0.891	0.929	4.26	15.83	19.08	20.51	27.08
Portland	0.873	0.900	3.08	18.91	18.06	-4.52	43.40
St. Mary	0.901	0.778	-13.67	18.92	18.76	-0.83	23.94
St. Ann	0.879	1.000	13.84	18.94	18.30	-3.37	34.57
Trelawney	0.896	0.857	-4.30	18.10	19.83	9.59	23.68
St. James	0.932	1.000	7.26	19.14	19.09	-0.27	42.86
Hanover	0.879	0.933	6.21	18.89	19.62	3.82	75.00
Westmoreland	0.898	0.889	-0.99	18.76	18.33	-2.30	38.46
St. Elizabeth	0.922	0.968	4.95	16.89	18.57	9.94	12.64
Manchester	0.921	0.851	-7.58	17.91	18.78	4.85	35.62
Clarendon	0.906	0.915	1.05	17.59	18.89	7.36	31.43
St. Catherine	0.910	0.882	-3.08	17.94	18.71	4.25	27.87
Correlation			0.0227			-0.1781	

Table 4: Dependent Variable: Probability of being enrolled in school

Variable	Full Sample	Males	Females	KMA	Other Towns	Rural
Exposure*Year	0.0124	0.120	-0.0492	0.221	-0.0467	0.0767
	(0.0750)	(0.112)	(0.0841)	(0.200)	(0.246)	(0.0945)
Year	-0.0539	-0.123*	-0.0148	-0.101	-0.0354	-0.111*
	(0.0398)	(0.0740)	(0.0372)	(0.126)	(0.118)	(0.0660)
Exposure	-0.0542**	-0.0637	-0.0427	-0.282**	0.0323	-0.0594*
	(0.0268)	(0.0603)	(0.0300)	(0.123)	(0.102)	(0.0324)
Age	-0.0482***	-0.0630***	-0.0349***	-0.0321***	-0.0452***	-0.0573***
	(0.00439)	(0.00662)	(0.00588)	(0.00850)	(0.00796)	(0.00522)
Male	-0.0153*			-0.0306*	0.000964	-0.0125
	(0.00803)			(0.0171)	(0.0191)	(0.0102)
Offspring	0.0176**	0.0199	0.0167**	0.00502	0.0150	0.0282**
	(0.00841)	(0.0162)	(0.00839)	(0.0153)	(0.0189)	(0.0114)
Household size	0.000756	-0.000274	0.00181	0.00370	-0.0105	0.00342
	(0.00278)	(0.00437)	(0.00326)	(0.00481)	(0.00665)	(0.00353)
Log per capita	0.0717***	0.0946***	0.0522***	0.0494***	0.0474***	0.0917***
Expenditure	(0.00837)	(0.0116)	(0.0105)	(0.0153)	(0.0145)	(0.0119)
Own House	0.00648	-0.00174	0.0124	0.00335	0.00904	0.00902
	(0.00825)	(0.0136)	(0.0106)	(0.0134)	(0.0168)	(0.0108)
No. of Women	0.00572	0.0107*	0.00157	0.00119	0.0112	0.00544
	(0.00390)	(0.00570)	(0.00457)	(0.00516)	(0.00840)	(0.00510)
No. of Children	0.00349	0.00504	0.00208	0.00138	0.0172*	-0.000251
	(0.00388)	(0.00557)	(0.00454)	(0.00794)	(0.0104)	(0.00458)
Rural#	0.0123	0.0296	-0.00179			
	(0.0128)	(0.0206)	(0.0148)			
Other Town#	0.00809	0.0250	-0.00644			
	(0.0127)	(0.0184)	(0.0185)			
N	2580	1297	1283	525	491	1564

Notes:

Numbers in parentheses are clustered standard errors; * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level

- Omitted reference category is KMA (Kingston Metropolitan Area)

$ - Marginal effect is the estimated impact of the variable on the probability of attending school, evaluated at the mean value of other variables.

Table 5: Dependent Variable: Number of Days Attended

Variable	Full Sample	Males	Females	KMA	Other Towns	Rural
Exposure*Year	-0.0512	0.0124	-0.119	-0.000744	-0.514**	-0.148
	(0.0841)	(0.134)	(0.0972)	(0.487)	(0.246)	(0.0920)
Year Effect	0.197***	0.132	0.242***	0.288	0.530**	0.193***
	(0.0632)	(0.100)	(0.0636)	(0.334)	(0.209)	(0.0686)
Exposure	0.0139	-0.00352	0.0324	-0.0299	0.179*	0.0629*
	(0.0322)	(0.0545)	(0.0359)	(0.118)	(0.102)	(0.0347)
Age	6.15e-05	0.00477	-0.00441	0.0137	-0.00374	-0.00498
	(0.00502)	(0.00783)	(0.00584)	(0.0136)	(0.00812)	(0.00540)
Male	-0.00877			-0.0161	-0.0183	-0.00400
	(0.0106)			(0.0289)	(0.0221)	(0.0128)
Offspring	-0.0190	-0.0253	-0.0118	-0.0252	-0.00774	-0.0183
	(0.0119)	(0.0191)	(0.0135)	(0.0259)	(0.0359)	(0.0135)
Household size	-0.00392	-0.00144	-0.00558	-0.00390	0.00740	-0.00599
	(0.00451)	(0.00767)	(0.00531)	(0.0125)	(0.00859)	(0.00652)
Log per Capita	0.0577***	0.0570***	0.0586***	0.0539**	0.0784***	0.0546***
Expenditure	(0.0104)	(0.0197)	(0.0103)	(0.0239)	(0.0180)	(0.0108)
Own House	0.0241*	-0.00169	0.0462***	0.0392	0.0393	0.00851
	(0.0131)	(0.0207)	(0.0137)	(0.0303)	(0.0259)	(0.0152)
No. of Women	0.0113**	0.0111	0.0116**	0.0100	-0.00992	0.0159**
	(0.00522)	(0.00863)	(0.00516)	(0.0143)	(0.0110)	(0.00762)
No. of Children	-0.00344	-0.00945	0.000864	0.00985	0.00443	-0.0100
	(0.00572)	(0.00929)	(0.00700)	(0.0146)	(0.0118)	(0.00660)
Rural#	-0.00224	0.0126	-0.0157			
	(0.0176)	(0.0273)	(0.0175)			
Other Town#	-0.00633	0.0123	-0.0201			
	(0.0200)	(0.0256)	(0.0254)			
N	2,298	1,119	1,179	483	440	1,375

Notes:
Numbers in parentheses are clustered standard errors; * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level
#- Omitted reference category is KMA (Kingston Metropolitan Area)

Table 6: Dependent Variable: Number of Days Attended

Variable	KMA Boys	KMA Girls	Other Town Boys	Other Town Girls	Rural Boys	Rural Girls
Exposure*Year	-0.188	0.0625	-0.350	-0.572**	0.0188	-0.417***
	(0.719)	(0.557)	(0.321)	(0.283)	(0.126)	(0.130)
Year	0.711	-0.0678	0.428*	0.566**	0.0855	0.272***
	(0.513)	(0.316)	(0.237)	(0.262)	(0.105)	(0.0690)
Exposure	0.0344	-0.0598	0.0859	0.229**	0.0120	0.146***
	(0.195)	(0.124)	(0.140)	(0.114)	(0.0471)	(0.0469)
Age	0.0277	0.00458	0.00760	-0.0154	-0.00530	-0.00514
	(0.0219)	(0.0135)	(0.0132)	(0.0108)	(0.00805)	(0.00607)
Offspring	-0.0476	-0.0145	-0.00580	-0.000112	-0.0246	-0.00990
	(0.0527)	(0.0281)	(0.0331)	(0.0542)	(0.0190)	(0.0169)
Household size	-0.00290	-0.00515	0.00579	0.00461	-0.000254	-0.0120**
	(0.0174)	(0.0124)	(0.0123)	(0.0115)	(0.0107)	(0.00553)
Log per capita Expenditure	0.0308	0.0676***	0.105***	0.0593***	0.0573***	0.0502***
	(0.0576)	(0.0186)	(0.0249)	(0.0228)	(0.0147)	(0.0172)
Own House	-0.0150	0.0831***	0.0346	0.0478	-0.00347	0.0238
	(0.0534)	(0.0269)	(0.0383)	(0.0376)	(0.0211)	(0.0186)
No. of Women	0.0247	0.00101	-0.00562	-0.00925	0.00880	0.0237***
	(0.0180)	(0.0127)	(0.0204)	(0.0105)	(0.0124)	(0.00790)
No. of Children	-0.00936	0.0273	-0.00102	0.0125	-0.0128	-0.00877
	(0.0252)	(0.0171)	(0.0200)	(0.0166)	(0.00862)	(0.00842)
N	217	266	220	220	682	693

Notes:
Numbers in parentheses are clustered robust standard errors; * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level

Table 7: Robustness checks: Dependent Variable: Days of school attended		
Variable	**Other Town Girls**	**Rural Girls**
(1) High vs Low Exposure	0.0494 (0.0584)	-0.1550 (0.0347)***
(2) Sample age 7-16	-0.3341 (0.2063)	-0.2110 (0.0738)***
(3) Cohort 9-12 (2002) vs 13-16(2006)	-0.3268 (0.3318)	-0.2897 (0.1092)***
(4) Cohort 8-11 (2002) vs 13-16(2006)	-0.2873 (0.2965)	-0.2289 (0.1077)**

Notes:
Numbers in parentheses are clustered standard errors; * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level