Gone With the Wind?
Hurricane Risk, Fertility and Education

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PRELIMINARY

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Abstract

This paper uses unique data on hurricanes in Guatemala to analyse how decisions on fertility and education respond to risks and shocks. Adults from areas with higher levels of risk have more education than those from areas with lower levels of risk, whether their parents owned land or not. Landed households show higher fertility with higher risk, while households without land have lower fertility. The higher fertility for landed households is not explained by higher mortality risk. Shocks affect both fertility and education negatively. If the shocks occur early in a woman's fertile period there is, however, a substantial compensatory effect later in life.

1 Introduction

Most households in developing countries face significant risks and uncertainty in almost all aspects of daily life, from income generation to basic survival. Furthermore, they often have little or no access to standard insurance against these risks. The economies are too poor to allow for governmentally provided insurance and most private insurance companies find the returns too low to make it attractive to offer their services to the poor. Hence, households are forced to find alternative strategies for dealing with risks and shocks, sometimes at a substantial cost (Morduch 1995).

Studying the strategies for coping with risk has been an active research areas in economics over the last couple of decades. Bliss and Stern (1982), Rosenzweig and Binswanger (1993) and Dercon (1996), for example, analysed the choice of farm inputs and crop choice in response to risk, while Fafchamps (1993) examined diversification of economic activities. Another strand of the literature has focused on migration and remittance responses to risk and shocks.[1] Examples of this line of research are Lucas and Stark (1985), Rosenzweig and Stark (1989), Paulson (2000) and Yang and Choi (2005). A household can also accumulate assets, such as savings, jewelry and farm animals, for later sale if an adverse income shock occurs as discussed in Cain (1981), Deaton (1992), Paxson (1992) and Rosenzweig and Wolpin (1993). Yet another possible way of coping with risk is to pool risk

[1]See Stark (1995) for a discussion of transfers between family members.

with other households as examined by, for example, Townsend (1994), Udry (1994) and Ligon, Thomas, and Worrall (2002). Finally, a household can adjust its labour supply to deal with a shock, both for adults as analysed by Kochar (1999) and for children as examined by Jacoby and Skoufias (1997), Guarcello, Mealli, and Rosati (2002) and Beegle, Dehejia, and Gatti (2003). The latter is especially of interest since a household might respond to a shock by taking their children out of school to work which may lead to lower educational attainment of the children.[2]

A reoccuring problem in the literature on risk coping is that while data on shocks are often available, it is significantly harder to capture risks. Hence, a substantial part of the literature essentially deals with how households respond to shocks rather than how they respond to risks. Furthermore, those studies that do deal with responses to risk have either focused on decisions which are repeated often such as crop choice, where one can use, for example, rain variability to capture risk, and/or used indirect approaches to assess how households respond to risk.

This lack of direct information on risk is important for two reasons. First, as discussed by Morduch (1995), there may be substantial costs associated with responses to risk which are not apparent if only information on shocks

[2]That shocks do affect a wide variety of activities can been seen in Hoogeveen, Klaauw, and Lomwel (2002), which finds some evidence that the timing of marriage and payment of bride wealth respond to income shocks in Zimbabwe, although the results are somewhat mixed possibly owing to the small sample used. Dekker and Hoogeveen (2002), in a related paper, finds that the timing of the *payment* of the bride wealth also responds to income shocks.

and their associated responses are availabe.[3] Furthermore, an analysis of the effects of shocks without information on risks, in essense confounds the effects of shocks and the effect of risk, which may have the opposite effect, due to the simple fact that an area hit by a higher number of shocks is, on average, also a more risk prone area.

Second, without information on risk it becomes difficult to analyse how "long-term" outcomes, i.e. decisions for which the outcome is only revealed with some delay or where the process is cumulative over time. Two important examples of such outcomes are education and fertility. The lack of reliable direct data on risk means that there so far has been little research on the effects of risks on these outcomes, despite a substantial literature on both topics generally focusing on developing countries.[4] Fertility and education are important components in both individual welfare and society's growth prospects and are likely to be significantly affected by a household's risk environment.

To analyse how decisions on fertility and education respond to both risk and shocks this paper uses unique data on hurricanes in Guatemala over the last 120 years combined with a household survey. Hurricanes is one of the

[3] One example is the choice of crops which leads to lower variability in income at the cost of a substantially lower average income over time. An analysis of the consumption response to shocks might then reveal little effect on consumption leading one to underestimate the true cost of risk.

[4] See Schultz (1997) on fertility and Schultz (1988) and Strauss and Thomas (1995) on education. Lindstrom and Berhanu (1999) analyse the effects of shocks, such as war and famine, on fertility in Ethiopia, but that is one of the few that examines the effects of shocks on fertility and there is to the best of my knowledge none that have looked at the effect of risk on fertility in developing countries.

most powerful of all weather systems.[5] They have a significant disruptive effect on all aspects of daily life and production, especially in agricultural areas where crops and infrastructure often are destroyed. Guatemala, together with many of the other Central American countries, faces very high annual risk of hurricane activity.

The outline of this paper is as follows. Section 2 discusses the theory and the possible implications of risk and shocks on both fertility and education. Section 3 covers the data used. The analysis of the effect of risk on fertility is presented in Section 4 and Section 5 presents the results for schooling. Finally, Section 6 concludes with a discussion of the implications of the results and suggestions for future research.

2 Theoretical Framework

This section outlines a model of parents' decisions on fertility and schooling under uncertainty. Previous research, such as Jacoby and Skoufias (1997) and Beegle, Dehejia, and Gatti (2003), analyse how income shocks and access to credit affect child labour and schooling decisions are influenced. How risk affects fertility and schooling have so far been ignored.

[5]The terms "hurricane" and "typhoon" are regionally specific names for a strong "tropical cyclone", which has sustained winds in excess of 64 knots (33 m/s). A tropical cyclone is the generic term for a non-frontal synoptic scale low-pressure system over tropical or sub-tropical waters with organized convection (i.e. thunderstorm activity) and definite cyclonic surface wind circulation (Holland 1993). In Guatemala the storms are called hurricane if the arrive from the east and cyclones if the arrive from the west. Due to the relative small size of the country is entirely possible to be hit by a hurricane on the west cost of Guatemala and vice versa for the cyclones.

A household derives utility from consumption in each period t, c_t, number of surviving children, n_t, and accumulated human capital of its children, H_{T+1}, where T is the last period the parents make decisions in. The parents' decision problem at $t = 0$ is to maximise expected discounted utility

$$E_0 \left\{ \sum_{t=0}^{T} \beta^t U(c_t, n_t) + \sigma(H_{T+1}) \right\}, \tag{1}$$

where β is the discount rate.[6] The period utility function, $U(c_t, n_t)$, has the standard characteristics with respect to consumption $U'_c(c_t, n_t) > 0$, $U''_{cc}(c_t, n_t) < 0$ and $U'_c(0, n_t) = \infty$. The human capital utility function is only concave, $\sigma'(H_T + 1) > 0$ and $\sigma''(H_T + 1) < 0$, with $\sigma'(0) < \infty$.

Assume that ϵ captures all information about an uncertain outcome, such as weather or economic conditions, and that its distribution function, $g(\epsilon)$, is known by the household. While future realisations of ϵ are uncertain, the household observes ϵ_t at the beginning of period t. This realisation of the uncertain outcome affects child survival, accumulation of human capital and income. I deal with each in turn.

Parents decide on the number of children, N_t, to have in each period. Parental inputs into child health, I_t, together with time invariant environmental factors, μ, and the uncertain outcome, ϵ_t, determines the number of

[6] This obviously ignores any intra-household distribution of resources among children. Ejrnæs and Pörtner (2004) examine how parents allocate resources within the family when fertility and schooling are endogenous.

surviving children,

$$n_t = N(N_t, I_t; \mu, \epsilon_t). \tag{2}$$

In each period parents chose how much time each child spends in school, s_t, with any remaining time spent working. Total time available per child is normalised to one. Accumulated human capital depends on the time a child spends in school, s_t, the stock of human capital at the end of the previous period, H_{t-1}, environmental factors, θ, and the uncertain outcome, ϵ_t,

$$H_t = H(s_t, H_{t-1}; \theta, \epsilon_t). \tag{3}$$

Finally, ϵ_t affects income generation, which also depends on children's time spent working, $1-s_t$, the number of children, n_t, and the human capital of children, H_{t-1}, and other household and local characteristics, η,

$$Y_t = F(n_t, 1 - s_t, H_{t-1}; \eta, \epsilon_t). \tag{4}$$

Chief among the household characteristics in η are the parents' education level and land holding of the household. Parents' leisure is ignored and their education level is constant over time.

Income is revealed at the beginning of the period and the household then decides on consumption, how many children, N_t, to have at cost, k, how much schooling to invest in their children, s_t, and how much to save, τ_t.

To capture the life-cycle aspect of education and fertility decisions, the children's wage is dependent on the amount of schooling they have, $w(S_t)$. While this may not be the most appropriate assumption while the children are very young, it helps to capture the trade-off betwen current income from child labour and future income when children might for example act as old-age security.

Finally, τ captures transfers between periods; τ_{t-1} is transfers from last period and τ_t is transfers from current period to the next period. The interest rate on these transfers is r. I discuss possible restrictions on these transfers below. With the available time per child normalised to one and a cost of schooling, p_s, the budget constraint becomes

$$Y_t + (1+r)\tau_{t-1} + n_t w(S_t)(1-s_t) = c_t + \tau_t + n_t p_s s_t + n_t k_t + n_t p_I I_t. \quad (5)$$

In the absense of any income risk this model is essentially the standard Becker and Lewis (1973) model of fertility with time dynamics added. Hence, we get the standard results on the trade-off between quality and quantity. An increase in the cost of children k, which can, for example, capture the time cost of the mother, leads to a decrease in the number of children and an increase in schooling. Furthermore, a decrease in the quality of schools or the return to education or an increase in mortality result in higher fertility and lower schooling.

["solve" model - bellman equation - FOC for that - derive implications]

2.1 The Effects of Risk on Fertility and Education

The most interesting case is when the household is faced with incomplete credit markets, so that they can save between periods but cannot borrow against future income (or their children's income). This seems to be a reasonable approximation of the situation in many developing countries where access and cost of lending money can be prohibitive.[7] One characteristics of hurricanes is that they not only affect income generation but most likely also will affect other factors that influence the fertility and education decisions, which is captured by θ for schooling and μ for mortality. In the absense of a significant amount of functional form assumptions the above model will provide few strong predictions that can be tested by data. It can, however, serve as a framework for discussing the likely effects of risk and shocks on fertility and education. We will examine four channels through which the risk of hurricanes can affect fertility and education. Those are mortality, returns to schooling, insurance and migration.

The first channel is through mortality, both child and adult. Hurricane risk can affect mortality risk through deaths during or immediately following the hurricane, which in the model above is captured by μ. The hurricane Stan in October 2005 is a good example. Guatemala was the hardest hit country with an official death toll of 652, although numbers as high as 2000 dead was mentioned, and an estimated 130,000 people were directly affected by the

[7] See Deaton (1992) for a discussion of the behaviour of consumption and savings under uncertainty in developing countries.

storm. Crops, livelihoods and homes were destroyed, and water sources compromised and two villages were completely buried under an avalanche of mud and rock. Furthermore, areas that were cut off by floodwaters and mudslides faced the threat of hunger and disease. As shown in, for example, Sah (1991) and Pörtner (2001) an exogenous increase in mortality risk increase fertility under certain reasonable assumptions. Hence, it is possible that higher hurricane risk can increase fertility to compensate for the expected mortality that might result from getting hit by a hurricane. Furthermore, given that an increase in mortality leads to a reduction in the expected return to investments in human capital, the expected effect of increased mortality is a decrease in schooling.

The second channel is risk induced changes in the return to education. To the extent that hurricanes destroy infrastructure or generate interruptions one would expect the "quality" of schooling to be lower in more hurricane prone areas than in less hurricane prone areas. Hurricanes might force school closures or displace the teachers or students. This leads to an increase cost of achieving a given level of human capital and the expected impact is a substitution toward quantity and away from quality of children. A similar effect might arise if more hurricane prone areas are also more likely to suffer from depressed economic development, since investors are presumable less likely to invest in more risky areas everything else equal. This would lead to a lower return to schooling than what would be found in similar areas with lower exposure to hurricanes.

There are, however, two effects that might lead to increased investments in education. The first is due to Schultz (1975), who argued that education might increase the ability to deal with disequilibria. Although the original argument was mainly aimed at invididuals in modernising economies a similar argument can be made for more risky areas in developing countries:[8] When a shock hits those who are better able to improvise and deal with the adverse situation are also most likely to fare the best. One way that schooling could help in this respect is by teaching the individual how to collect and process information. The same would be the case for analytic ability to the extent that it can be acquired through schooling. As mentioned above an area with higher hurricane risk might see less investment in physical capital than a similar area with lower hurricane risk. Presumably the reason for this lower level of investment would be the risk of losing the physical capital when a hurricane hits. Human capital is, however, arguably less prone to be destroyed by hurricanes than physical capital. Hence, the second effect is that higher risk of hurricanes increases the return to human capital relative to physical capital which would tend to increase education levels.[9] Interestingly, the expected effect of both of these effects on the return to human capital is negative. Hence, it would be possible to observe high levels of education and at the same time low returns to education when measured by wages during

[8] Related arguments can be found in Rosenzweig (1995) and Foster and Rosenzweig (1996).

[9] An example at the national level is the relatively quick recovery of Europe after the second world war, which is attributed to the high level of human capital, which had suffered less from the war than the physical capital.

"normal" times. We will return to this later on.

In the absence of perfect capital and insurance markets parents might rely on their children as a means of insurance, both while the children are still at home and later in life as old-age security. Children can help either by working on the farm or as wage labour. Both Jacoby and Skoufias (1997) and Guarcello, Mealli, and Rosati (2002) present evidence that parents decrease children's schooling and increase their time spent working when the household experiences a shock. In a similar vein Beegle, Dehejia, and Gatti (2003) show that credit-constrained households in Tanzania respond to transitory income shocks by making their children work more. That children work more as a response to shocks is, of course, a necessary but not sufficient condition for children to serve as substitutes for insurance. It is likely that children will mainly serve as a substitute for insurance for landed households. Hurricanes destroy crops, buildings and land (the latter mainly through mudslides) and replanting and rebuilding farm buildings are often very time sensitive since delays can ultimately mean a completely failed harvest followed by food shortage or at least a significant reduction in profit. The question then is why a farmer cannot rely on hired labour to help with replanting and rebuilding. One answer is that during crisis situations such as when a hurricane hits it is often difficult, if not impossible, to enforce labour contracts, but family members have an incentive, beside altruism, to help since they would otherwise also suffer.[10] Pörtner (2001) describes in more detail how children can

[10]The lack of enforcable labour contracts is not only a problem in developing countries

serve as substitutes for imperfect or missing insurance market.

The main outcome of interest here is that the insurance argument indicate that households faced with higher risk would have more children. Note, however, that even if the children are not strictly speaking insurance, in the sense that they produce more than they consume during shocks, the fact that they can help on the farm reduces the cost of having children and therefore should increase the demand for children. Furthermore, we would expect educational attainment to be lower in this case for two reasons. First, following the standard quantity-quality argument we expect that the higher number of children due to the "insurance effect" leads to reduced investments in education. Second, when a shock hits children will be taken out of school to work on the family farm, which, everything equal, is likely to reduce how much schooling they receive.

Beside having the younger children work more and go to school less when hit by a shock it is also possible that older children who either have their own household or have migrated can make transfers to their parents.[11] This is akind to the old-age security argument in which parents have depend on their children for support during old age. It is likely that parents in areas

as the example of the 2005 Hurricane Katrina in the US shows. Rivlin (2005) describes the how even with significant hiring bonuses and significantly increased wage it can be next to impossible to attract workers in New Orleans. Another example is the following quote from Cridlin (2004) describing the situation during Hurricanes Charley and France in 2004: "You don't want to stay here with your family if it's not safe,... but if you don't stay here and keep those pumps running, nobody's going to."

[11] Children can also be used to create connections with other families, thereby forging an mutual insurance relationship as explored in Rosenzweig and Stark (1989).

with higher risk of hurricanes also have a greater need for old-age support, especially after a shock hits. The old-age security argument has an ambigious effect on fertility and schooling. On one hand, if children are important as old-age security and mortality is a significant risk then parents will have more children to ensure that at least a certain number survives to be able to support their parents later in life. On the other hand, it may be better for the parents to invest in education of their children since that will increase their income as adults and therefore presumably will lead to higher transfers to the parents.

The final channel through which hurricane risk can affect fertility and education is migration. There are two main ways that this can happen, migration by parts of the household to reduce exposure to risk or to smooth consumption after a shocks has hit, and migration of the whole household in response to risk. The first is the most familiar and has received a significant amount of attention in the literature.[12] How this affects fertility and education depends on the return to education in the receiving areas and the correlation of shocks between the originating and receiving area. One might imagine that a household that has the choice to send a household member to the closest city or to another agricultural area. Presumably the return to education is higher in the city, but if the city has a high covariance with the originating area it might be better for the household to send its migrant to

[12]See, for example, Stark (1991). A related argument is given for daughters marriage migration in India by Rosenzweig and Stark (1989).

the other agricultural area. In the latter case it is not clear that migration for risk diversification reasons should necessarily lead to higher investments in education. Furthermore, if parents are not convinced that all their children will remit once they have migrated they might have more children than they otherwise would.[13]

The risk of hurricanes might also induce the whole household to move. There is a number of different ways this can happen. First, households that are somehow less able to deal with risks might be more likely to move, leaving households that are more fit for the environment. It is not clear how this will affect fertility and education levels. On one hand, if less prepared means households with lower fecundity and/or lower preferences for children, then we would expect to see larger households in areas with higher risk of hurricanes, since it is more expensive for those households to insure themselves using children. A similar argument can be made in terms of innate ability for schooling if education helps one deal with the risk. On the other hand, it is also possible that more risk averse households move out of the higher risk areas leaving those households who are less risk averse. These latter households will pay less for insurance, which would then lead to lower number of children and/or less education depending on which of these factors, if any, are important in smoothing income and consumption. The main reason this argument is of interest here is that it will affect the effectiveness of policies

[13]For further discussion of why migrants remit, such as altruism and self-enforcing contracts, see Lucas and Stark (1985), Stark (1991, ch. 15), Cox and Stark (1994) and Lillard and Willis (1997).

put in place. Imagine a situation in which state provided insurance against hurricane risk is offered. If "evoluationary" migration is important the effect of the policy might be smaller than predicted.

While there are a number of different possible prediction of how fertility and education responds to risks the effect of a hurricane shock is easier to predict. Since hurricanes lowers income during the current period we expect that both fertility and schooling decreases after a hurricane. The mechanism is simple: As consumption decreases the shadow price of both having a child and sending children to school increases, which leads parents to substitute towards consumption and away from children and education. Note, however, that this argument is to some extent a question of the timing of both education and fertility. Parents can, at least partly, make up for the temporary reduction by having children longer and making their children work less in subsequent periods.

[sum up effects/expectation for fertility and education]

3 Data

Two types of data are required for this analysis. The first is household data with information on fertility and children's education. The second is information on the risk environment and shocks occurred which can be linked to households (or at least a well-specified and preferable small geographical area in which the household resides). We discuss each in turn.

The household data are from ENCOVI 2000, which is a LSMS-style nationwide household survey from Guatemala collected in 2000. The survey covered 7,276 households, of which 3,852 were rural and 3,424 were urban. It was designed to be representative both at national and regional levels and in urban and rural areas.

Most of the effects of risk on fertility and education appear to be more applicable to rural areas than to urban areas and we therefore focus on rural areas. Guatemala has, however, relatively little urbanisation and even areas that are characterised as urban often have a very strong rural component.[14] The main sample therefore includes all "urban" sectors where at least one household owns or rents land, with the exception of sectors in the Municipality of Guatemala, which covers the capital of Guatemala, which is exluded completely.[15] The results remain qualitatively the same if we restrict to strictly rural household, but the standard errors are larger.

ENCOVI 2000 collected information on fertility from all women between 12 and 49 years of age.[16] One drawback is the lack of information on the timing of births, which is restricted to a question about when the last birth took place. It is possible to get more information on timing through the date of birth if the child is alive and still living with the mother. For children who

[14]Urban is defined as the Municipality of Guatemala Department and officially recognized centres of other departments and municipalities.

[15]The number of surveyed households in a sector is between 6 and 12 and a sector is always declared to be either urban or rural in the original data. There are 22 departments in Guatemala with a total of 331 municipalities, of which we use data from 205 of them.

[16]There are three questions on fertility: The number of pregnancies, the number of children ever born and the number of children alive at the time of the survey.

have either died or left the household there is, however, no information. This implies that the sample of children on which we have educational information is not a complete sample of all children born. Hence, instead of using children's education we take advantage of the fact that the ENCOVI 2000 is a representative survey of the population and examine the effect of risk on the educational attainment of the adult population.[17] This is possible because the survey contains information on municipality of birth, information on parents and how long an individual has lived in an area.

Even though the fertility and education information may not be optimal there is one major advantage of this survey, which is secondary data that allow us to calculate risks and shocks at a disaggregated level.[18] The secondary data were collected for a report, UNICEF (2000), on natural disasters and vulnerability in Guatemala. The raw data consist of a listing of natural disaster events, mostly drawn from written sources such as newspapers, with information on the type of event, the date, the area hit, the source of the information and a short description of the event. What is interesting here is that for most of the events the information cover very long periods of time.[19] Beside the long time span covered, a major advantage of these

[17]We discuss potential problems with this approach below.

[18]The household and the associated community survey do contain questions on exposure to shocks, but these only cover the 12 month period prior to the survey date for the household questionnnaire and the period 1995 and 2000 for the community questionnaire. These periods are, however, too short for our purposes.

[19]The longest period covered is for earthquakes and volcanos, which covers the period 1530-1999. Although there clearly are problems with a measure that claims to go back to 1530 this is one of few ways to get a reasonable measure of the risks in an area (or rather the perceived risk by people).

data is that they have information at municipality level allowing a relatively precise measure of the risks and shocks a household is exposed to.

The main variable of interest here is the measure of risk of hurricanes.[20] Risk is calculated as the percentage probability of an event occurring in a year, based on events from 1880 to 1997. The first recorded hurricane in the data set is in 1880. As can be seen from the effect of hurrican Mitch these storms can be very destructive and hit essential everywhere in Guatemala. There are, however, substantial variation in how likely a municipality is to be hit by a hurricane as we will see below when we discuss the descriptive statistics for the data.

A problem with these data is likely to be underreporting of events. This is especially a problem in less populated areas since there are fewer people to report the event in the first place and since the event might not be reported in printed sources if few people were affected. Hence, areas that were previously sparsely populated may be assigned a lower risk measure than the true one, although this also may mean that people moving in to the area has less reason to expect a high level of risk. Furthermore, only major events are likely to be reflected and this problem become more pronounced the further back in time one tries to get information on. We will return to the effects of these measurement problems on the results below.

[20] We will return to the definition of shocks below since that depends on the dependent variable of interest.

4 The Effects of Risks and Shocks on Fertility

This section analyses the determinants of fertility. We first discuss the econometric model and selection of sample. Second we present the variables, their likely impact on fertility and why some commonly used variables are excluded. Finally, we present and discuss the results.

ENCOVI 2000 includes three measures of fertility for each women: The number of pregnancies, the number of live births and the number of children alive at the time of the survey. The number of live births obviously comes closest to the choice variable in the model, but the number of surviving children is probably the best indicator of what the household is most likely to care about, especially if children are needed as "insurance" as discussed above (either through their labour when a hurricane hits a farm or through their income as migrants). The number of pregnancies is probably less precisely measured than the two other variables and might indicate the health status of the mother more than what we are interested in .[21] Hence, the estimations are done for the number of births and children alive. The majority of women surveyed were still in their fertile years, 15-44 years of age, at the time of the survey and hence, what is used are not the completed fertility measures, but the cummulative age-specific fertility as we discuss below.

[21]A less healthy mother is likely to have more pregnancies per life birth than a healthy mother.

The estimated equation is

$$F_i = \alpha + X_i'\beta + R_i'\gamma + S_i'\delta + \varepsilon_i, \tag{6}$$

where F is the fertility outcome of interest, X is a vector of individual and household variables, R is a vector of risk, including interactions with individual and household variables and S measures shocks. We estimate (6) using OLS with robust standard errors where the cluster level is the household. Two advantages of OLS over count models such as the Poisson model are the less restrictive nature of the assumptions needed and that the effects are easier to interpret. The results remain qualitatively the same if using a Poisson model instead.[22] Even though data on fertility is available from all women aged 12 to 49 years of age we restrict the sample to women aged 15 to 49, since the number of births is very small between age 12 and 14.

4.1 Variables

Table 1 presents the descriptive statistics for the variables used in estimating equation (6). As mentioned above the explanatory variables fall into three groups: Individual and household variables, risks and risk interactions and finally shocks. We discuss these after examining the dependent variables.

Even though Guatemala has a total fertility rate of around 4.6 the average number of births in the sample is 2.8, which is due to the the large number

[22]The results are available on request from the author on request.

of women still in their reproductive ages in the sample.[23] The number of surviving children reflects a death rate of around eight percent. Guatemala's infant and child mortality rates in 2003 were around 35 and 47 per 1000 children born, respectively. The higher number of deaths in this sample reflects both that the rural nature of the sample and that it includes all deaths, event those after age 5.

Table 1: Descriptive Statistics — Fertility

Variable	Mean	Std. Dev.
Number of births	2.8439	3.0222
Number of children alive	2.5900	2.6970
Age	28.0223	9.8763
Age^2	882.7747	605.1320
Indigenous	0.4543	0.4979
Owns land	0.4687	0.4991
Rural	0.6704	0.4701
Risk of hurricane (percent)	4.6314	0.9641
Risk of hurricane × owns land	2.2269	2.4383
Risk of hurricane × age	129.5761	53.6699
Risk of hurricane × age^2	4077.6569	2976.7369
Risk of hurricane × age × owns land	62.4472	76.0640
Risk of hurricane × age^2 × owns land	1981.4085	2986.5069
Hurricane shocks (before age 30)	0.8034	0.6666
Hurricane shocks × age 35-49	0.2981	0.7041
Hurricane shocks × owns land	0.3798	0.6118
Hurricane shocks × age 35-49 × owns land	0.1533	0.5182

As mentioned above risk is calculated as the percentage annual risk of a hurricane. The mean probability is around 4.6 percent per year, with the minimum being 3.4 and the maximum 7.6 and the standard deviation just short of 1. While these numbers may not appear very substantial at first, there are two things to consider. First, for the highest risk areas a woman

[23]The average number of births for women aged 45 and older is 5.5.

would expect to see more than two hurricane during her fertile ages and around four from age 15 to retirement age, while the corresponding numbers for the lowest risk areas are one and just below two. Second, a higher risk of hurricane most likely is correlated with a higher risk of other storms. Only those storms with strong enough winds will be classified as hurricanes, but for every hurricane there is likely to be a number of smaller storms which may be also destructive, albeit not on the same scale.

While risk of hurricane may not have a theorectically predictable effect on fertility, at least given the relatively few assumption we impose above, the hypothesis, based on the model, is that all significant shocks have a negative impact on fertility. We measure shocks as the number of occurances between the year the woman enters her fertility period (taken to be 15 years) and her 29th year or survey year, whatever is first. The reason for the 29 year cutoff is that the majority of women have most of their children before they turn 30, although there are a number of women who continue having children until their are 45. Furthermore, as we discuss below, this allows us to examine whether there is a "catch up" effect later in life. The average number of shocks for the 15 year period during the early fertile period is 0.8, with a standard deviation of 0.7 and a minimum of zero and a maximum of 5. This is in line with the predicted number of shocks based on the risk measure, in that a woman exposed to the average risk would expect to see around 0.7 hurricanes during the 15 year period.

The individual and household characteristics are age, ethnicity and land ownership, area of residence, altitude and geographical region. We discuss each variable in turn. Since the fertility measures are cummulative and not completed fertility we include the woman's age and her age squared.[24] Beside the regular direct effect of age on fertility there are three way that risks can interact with age. First, women can begin having children earlier than they would otherwise have. Second, they can continue having children later in life. Finally, they can have children more closely spaced. To capture these effects we interact the mother woman's age and age squared with the risk measure.

Another effect of age is the possibility of a "catch-up" effect. Women who have been exposed to a shock while relatively young could compensate for the expected negative impacts on fertility.[25] We therefore interact a dummy for being between 35 and 49 years old at the time of the survey with the number of shocks experienced while the woman was between 15 and 29 years of age. To the extent that women are able to compensate for shock by having children later in life we would expect the interaction to be positive.

Ethnicity is here captured by a dummy for belonging to an indigenous group with the excluded group being the ones who classify themselves as "ladino". The majority of the indigenous are various groups of Mayan with a very small number who are Garifuna or Xinka. For our sample the indigenous group comprises sligthly less than half of all the women in the sample.

[24]An alternative is to use age dummies. That would be more flexible, but would not easily allow for interactions with the risk measure.

[25]Recall that the number of shocks between age 15 and 29 is the measure of shocks.

The main household characteristics we include is ownership of land. There are two variables in the survey that capture how much land a household has: The area owned and the (self-evaluated) value of this land. The value of land may, however, change over time and the quality of land can vary widely even within small geographical areas. Hence, we use a dummy variable for whether the household owns land. Just less than half of the sample live in households that own land.

Beside the direct effects of access to land on fertility we expect that both risks and shocks have different effects on those households that own land and those that do not. Following the arguments above children will generally serve best as insurance if a household owns land since we argue that children serve a special role during the immediate aftermath of a hurricane. Hence, we expect those households with land to show a positive effect on fertility of hurricane. To capture this and other possible differences we interact the risk and shocks measures with the land dummy variables. In addition we interact age and age squared with the interaction between land ownership and risk. Finally, we interact shocks with the interaction between owning land and the dummy for being 35 to 49 years of age to examine whether there is a difference in the compensation in fertility after a shock between the two groups.

A potentially important issue is whether the risks measure described above captures only the risks or whether they also pick up unobservable area characteristics which might influence the fertility decisions of the households. First, we use dummies for the 22 departments with the Guatemala Department, where Guatemala City is located, being the excluded variable.[26] This, however, only account for some of the geographical variation and we therefore also include a fourth-order polynomium in altitude in meters. The main reason for included altitude is that it is an important factor in what type of crops can be grown in an area, something which might affect the fertility decision directly.[27] Finally, we include a dummy for the household being in a purely rural area. The reason that the rural dummy is not interacted with the other variables, especially the risk and shocks variables, is that these interactions add very little to the overall results, except by increasing the standard errors of the estimated parameters. This is to be expected given that the so-called urban areas that are included in the sample have a substantial amount of agricultural activity in them.[28]

Before moving on to the results is it worth discussing some of the explanatory variables which are not included and why. In the individual and household characteristics some would consider whether a woman is married to be a relevant variable. Marital status is, however, not be an appropriate

[26] Using department dummies can also partly capture the effect of the civil war, which began in 1960 and lasted 36 years and resulted in more than 200,000 dead. The disruption and turmoil resulting from the civil may have a substantial impact on both fertility and education, but finding a suitable way of capturing these effects is difficult. The five departments with the highest number of massacres were Chimaltenango, Huehuetenango, Quiche, Baja Verapaz and Alta Verapaz.

[27] Since there is little directly relevant information in the estimated parameters for department and altitute we do not presents these in the descriptive statistics or in the results below. The full tables are available from the author on request.

[28] Results with the interactions are available from the author on request.

explanatory variable since it is closely connected with the decision to have children and it therefore determined by the same factors. Including an endogenous variable may lead to bias in both the affected parameter *and* the other estimated parameters. Having rented land is also likely to be endogenous to the decision on how many children to have and the same is the type of crops grown.

A similar argument can be used for most other individual and household variables not included. The most controversial is probably the exclusion of the mother's education as an explanatory variable. Since the parents of the women surveyed were likely faced with the same risk environment as the women and this influenced their decisions on fertility and education, the woman's education is endogenous and it therefore excluded. We estimate the determinants of adult education below using the same risk measure and it would therefore be inconsistent to assume that the mother's education is exogenous.[29]

Most of the regularly included community variables, except type of region and the civil war dummy, have also been left out. The argument for that is that the risk environment is likely to have a significant effect on how a community develops. A community which has a significant risk of hurricanes may, for example, be less likely to have a well developed infrastructure. Hence, if we included infrastructure as an explanatory variable we would not

[29]The results for the determinants of fertility with the mother's educational attainment and its square show qualitative similar results and are available upon request.

capture the full effect of risks and shocks on mothers' behaviour.[30]

Finally, we do not control for infant and child mortality in the area. There are two reasons for this. First and most importantly, as for the infrastructure, it is highly likely that infant and child mortality is significantly affected by the risks and shocks that an area is exposed to making it endogenous. Second, in order to assess the effects of hurricane on mortality we estimate precisely this relationship below to check if this can explain the effect of the risk of hurricanes on fertility, which we can do since we have information on both number of children born and the number of children alive.

4.2 Results

We present the results for the number of children born in Table 2 and the results for the number of children alive in Table 4.2. For each fertility variable we show seven different specifications or models. The first is the baseline regression with the background variables. The second and third add risk and risk interacted with land ownership, while Model IV furthermore includes the age and risk interactions, both on their on own and interacted with land. Specifications V-VII are the same as II-IV, but with the shocks added. Model V has just the shocks and shocks interacted with being 35 to 49 years of age, while VI and VII also include these two shocks variables interacted with land ownership.

The main parameters of interest are the risk measure and the interactions.

[30] [Current discussion in growth literature on climate and institutions]

Table 2: Effects of Risks and Shocks on Fertility

	Model I	Model II	Model III	Model IV	Model V	Model VI	Model VII
Age	0.3902***	0.3902***	0.3902***	0.2164**	0.4515***	0.4579***	0.2480***
	(0.0188)	(0.0188)	(0.0188)	(0.0871)	(0.0453)	(0.0457)	(0.0907)
Age squared	−0.0028***	−0.0028***	−0.0028***	−0.0008	−0.0039***	−0.0040***	−0.0014
	(0.0003)	(0.0003)	(0.0003)	(0.0015)	(0.0009)	(0.0009)	(0.0016)
Indigenous	0.4639***	0.4627***	0.4609***	0.4615***	0.4587***	0.4604***	0.4562***
	(0.0687)	(0.0691)	(0.0691)	(0.0688)	(0.0688)	(0.0686)	(0.0685)
Owns land	0.0305	0.0315	−0.5042*	−0.5368*	0.0311	−0.3109	−0.3163
	(0.0620)	(0.0621)	(0.2964)	(0.2944)	(0.0616)	(0.3077)	(0.3084)
Rural	0.8414***	0.8413***	0.8331***	0.8329***	0.8404***	0.8350***	0.8304***
	(0.0571)	(0.0571)	(0.0572)	(0.0571)	(0.0568)	(0.0569)	(0.0567)
Hurricane risk (%)		−0.0156	−0.0525	−0.6154**	−0.0142	−0.0469	−0.6478**
		(0.0692)	(0.0704)	(0.2508)	(0.0691)	(0.0699)	(0.2689)
Risk × owns land			0.1164*	−0.1002		0.1021	−0.1619
			(0.0623)	(0.1150)		(0.0624)	(0.2329)
Risk × age				0.0341*			0.0360*
				(0.0195)			(0.0210)
Risk × age^2				−0.0004			−0.0005
				(0.0003)			(0.0004)
Risk × age × owns land				0.0069			0.0109
				(0.0080)			(0.0191)
Risk × age^2 owns land				0.0000			−0.0000
				(0.0001)			(0.0004)
Hurricane shocks (age 15 - 29)					−0.4379***	−0.2515***	−0.2909***
					(0.0824)	(0.0945)	(0.1127)
Shocks × age 35 - 49					0.4036**	0.0991	0.2676
					(0.2001)	(0.2107)	(0.2765)
Shocks × owns land						−0.4255***	−0.3323**
						(0.0975)	(0.1618)
Shocks × age 35 - 49 × owns land						0.7021***	0.1736
						(0.1234)	(0.3986)
Constant	−6.5008***	−6.4360***	−6.2855***	−3.1542***	−6.9591***	−6.9365***	−3.3452***
	(0.3201)	(0.4386)	(0.4422)	(1.1489)	(0.6117)	(0.6157)	(1.1763)
Observations	6648	6648	6648	6648	6648	6648	6648
R-squared	0.57	0.57	0.57	0.57	0.57	0.57	0.58
Adj. R-squared	0.56	0.56	0.56	0.57	0.57	0.57	0.57
Log-Likelihood	−14009.39	−14009.36	−14007.30	−13956.83	−13985.22	−13958.31	−13923.52
Joint F-test for Risk × age = 0 and Risk × age^2 = 0				5.87***			6.41***
Joint F-test for Risk × age × owns land = 0 and Risk × age^2 × owns land = 0				31.49***			21.75***

NOTE: * significant at 10%; ** significant at 5%; *** significant at 1%; Robust standard errors in parentheses, clustered at the household level. Additional variables (not shown) are department dummies and a fourth-order polynomial in altitude.

Table 3: Effects of Risks and Shocks on Number of Children Alive

	Model I	Model II	Model III	Model IV	Model V	Model VI	Model VII
Age	0.4055***	0.4056***	0.4057***	0.2141***	0.4619***	0.4663***	0.2482***
	(0.0168)	(0.0168)	(0.0168)	(0.0785)	(0.0408)	(0.0412)	(0.0822)
Age squared	−0.0035***	−0.0035***	−0.0035***	−0.0010	−0.0045***	−0.0046***	−0.0017
	(0.0003)	(0.0003)	(0.0003)	(0.0014)	(0.0008)	(0.0008)	(0.0015)
Indigenous	0.3173***	0.3150***	0.3133***	0.3139***	0.3108***	0.3116***	0.3078***
	(0.0623)	(0.0626)	(0.0626)	(0.0624)	(0.0622)	(0.0621)	(0.0620)
Owns land	0.0367	0.0386	−0.4820*	−0.5193**	0.0384	−0.2995	−0.3261
	(0.0557)	(0.0558)	(0.2664)	(0.2642)	(0.0552)	(0.2771)	(0.2764)
Rural	0.7206***	0.7204***	0.7124***	0.7127***	0.7197***	0.7136***	0.7104***
	(0.0519)	(0.0519)	(0.0520)	(0.0519)	(0.0515)	(0.0515)	(0.0514)
Hurricane risk (%)		−0.0299	−0.0658	−0.6669***	−0.0274	−0.0605	−0.7445***
		(0.0622)	(0.0635)	(0.2255)	(0.0619)	(0.0629)	(0.2408)
Risk × owns land			0.1131**	−0.0541		0.1017*	−0.0124
			(0.0560)	(0.1033)		(0.0559)	(0.2049)
Risk × age				0.0388**			0.0447**
				(0.0175)			(0.0188)
Risk × age^2				−0.0006*			−0.0007*
				(0.0003)			(0.0003)
Risk × age ×				0.0053			−0.0002
owns land				(0.0072)			(0.0169)
Risk × age^2				0.0000			0.0002
owns land				(0.0001)			(0.0003)
Hurricane shocks					−0.4361***	−0.2694***	−0.3394***
(age 15 - 29)					(0.0741)	(0.0853)	(0.1011)
Shocks × age 34 - 49					0.3801**	0.1325	0.3762
					(0.1819)	(0.1909)	(0.2505)
Shocks × owns land						−0.3749***	−0.2328
						(0.0899)	(0.1439)
Shocks × age 35 - 49 ×						0.5618***	−0.0593
owns land						(0.1107)	(0.3546)
Constant	−6.5005***	−6.3760***	−6.2297***	−3.0370***	−6.8486***	−6.8072***	−3.2353***
	(0.2895)	(0.3931)	(0.3973)	(1.0351)	(0.5528)	(0.5571)	(1.0640)
Observations	6648	6648	6648	6648	6648	6648	6648
R-squared	0.55	0.55	0.55	0.56	0.56	0.56	0.56
Adj. R-squared	0.55	0.55	0.55	0.55	0.55	0.56	0.56
Log-Likelihood	−13363.51	−13363.38	−13361.02	−13321.09	−13333.07	−13311.98	−13280.84
Joint F-test for Risk × age = 0 and Risk × age^2 = 0				6.14***			6.77***
Joint F-test for Risk × age × owns land = 0 and Risk × age^2 × owns land = 0				24.89***			18.33***

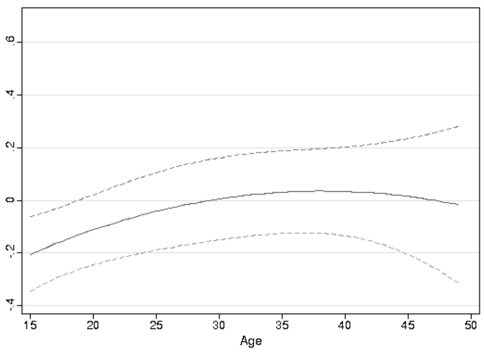
NOTE: * significant at 10%; ** significant at 5%; *** significant at 1%; Robust standard errors in parentheses, clustered at the household level. Additional variables (not shown) are department dummies and a fourth-order polynomial in altitude.

Overall the results for the two outcomes are very similar. In the basic models (II and V) there is no significant effect of risk on fertility. This, however, changes dramatically if one adds an interaction between risk and land ownership (III and VI). An increase in the risk of a hurricane leads to statistically significant increases in fertility for households that own land, while there is a negative but not statistically significant effect on those without land. For both Models III and VI the size of the effect is, however, relatively small. To provide an idea of the magnitude consider a one percentage point increase in the risk of a hurricane. This would lead to increase in the number of children of only about 0.05 for land-owning households. Remember, however, that this result is based on the entire sample of women aged 15 to 49 and it likely that the main way to increase fertility is by continuing to have children later in life.

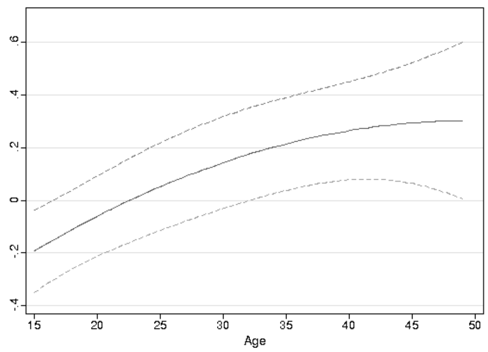
One way to get around this problem is to introduce the interactions between the two age variables and the risk and risk interacted with land. This is done in Models IV and VII. The main drawback is that since the effect is no longer linear it is difficult to interpret the effects of an increase in hurricane risk. Figures 1 and 2 therefore presents the estimated marginal effects of an increase in hurricane risk by age for number of children ever born and children alive at the time of the survey together with the upper and lower bounds of the 95 percent confidence interval.[31] For both figures (a) and (b) are for Model IV, which is the specificatin without shocks, and (c) and (d)

[31] The confidence interval is calculated using the delta method.

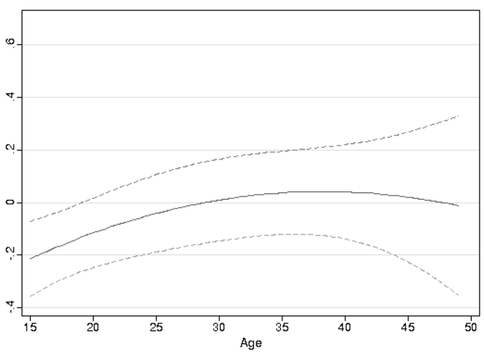
are for Model VII, which includes the shock variables.



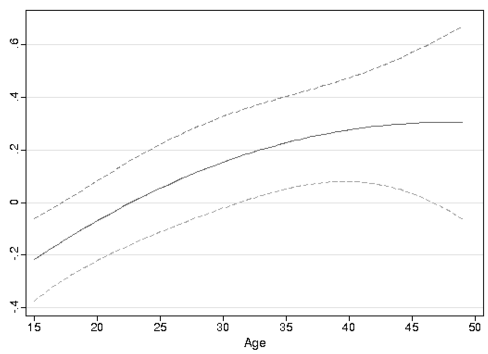
(a) Model IV for Landless



(b) Model IV for Land Owners



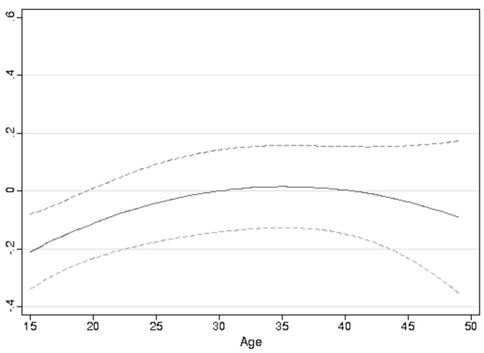
(c) Model VII for Landless



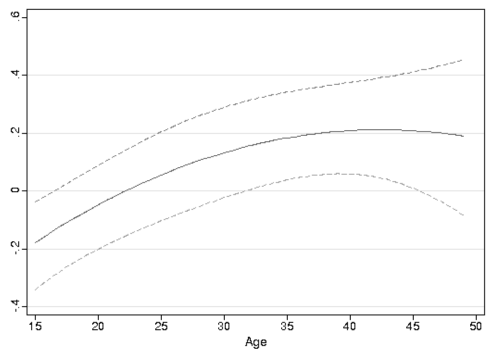
(d) Model VII for Land Owners

Figure 1: Marginal Effect of Hurricane Risk on Number of Children Born

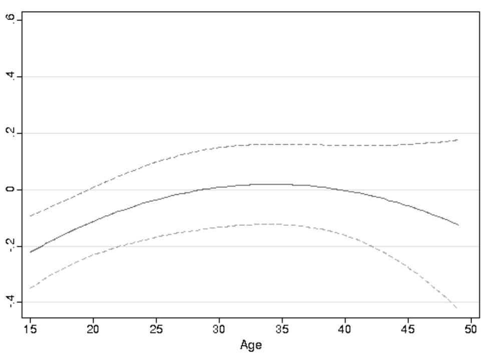
As we would expect from the previous results there is no significant effect of hurricane risk on either fertility or children alive for households without land. The one cave-at to this result is that there does appear to be a tendency for very young women to have fewer children in areas with higher risk of hurricanes and this holds for both household with and without land. This effect is statistically significant until around age 18 and one possible inter-



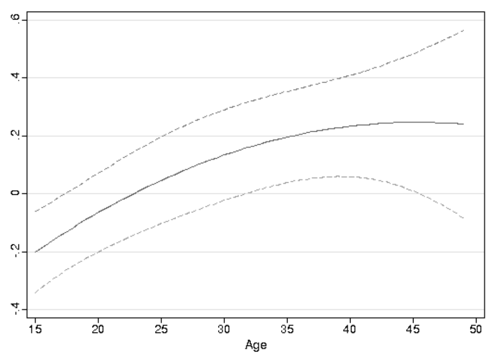
(a) Model IV for Landless



(b) Model IV for Land Owners



(c) Model VII for Landless



(d) Model VII for Land Owners

Figure 2: Marginal Effect of Hurricane Risk on Number of Children Alive

pretation is that women in more risk prone areas postpone their childbearing compared with women with similar characteristics in less risk prone areas. We will return to explanations for this results when we analyse the effect of risk on educational attainment.

The main result is how the risk of hurricanes affects the number of children born and the number of children alive for households that own land.[32]

[32]Since the results are essentially the same for the four different versions focus here is on Figure 1(a).

The predicted marginal effect of hurricane risk on fertility is positive from around age 23 and it becomes statistically significant at age 32 and remains statistically significant after that.[33]

Hence, there is clear evidence that higher hurricane risk leads to higher fertility for households with land. Furthermore, the estimated effect of hurricane risk on fertility is now substantial. If we take the number of children born to a woman aged 45 or above as a close approximation to the completed fertility the marginal effect of a one percentage point increase in fertility is now about 0.3 children.[34] With a more than four percentage points difference between the highest and the lowest risk areas this corresponds to an increase of more than one child. For comparision the average number of births in the sample for women aged 45 and older is 5.5 as mentioned above. As expected the effect on the number of children alive is somewhat lower but still substantial, providing a first indication that mortality is not the main reason for the higher number of children in more risk prone areas.[35]

As mentioned above, Models VI-VII show the results when including shocks, which is measured as the number of hurricanes during the mother's

[33]For the other three figures the effect becomes statistically insignificant at the 95 percent level although only slightly so at or after age 45. The most likely explanation for this increase in the confidence interval is that, consistent with the young age distribution in Guatemala, there are relatively fewer older women compared to younger women. Women age 45 to 49 comprise less than ten percent of the sample. While it is clear that women in higher risk areas continue to have children longer it is not possible to determine if the children are also more closely spaced.

[34]Recall that a one percentage point increase is about one standard deviation.

[35]The relation between hurricanes and child mortality will be discussed in more detail below.

main childbearing years (15 to 29 years of age). As expected the number of hurricanes has a large and statistically significant negative effect in all three models. In model V each hurricane reduces the number of children born by just over 0.4. Interacting the number of hurricanes with land ownership shows that most of the reduction is due to lower fertility in households that own land. The effect for households without land is now about 0.25, which is still statistically significant, while the reduction in the number of children for women in land owning households is around 0.65 per hurricane, which is very strongly statistically significant.

The reduction in fertility following a hurricane is, however, only part of the story. The interaction between the number of hurricanes and being between 35 and 49 years old at the time of the survey shows that the mother is able to, at least partly, compensate for the reduction in fertility following the shock by having the children later. It is impossible to reject that the combined effect of the number of hurricanes and the interaction with being older is statistically significantly different from zero, since Model VII shows a only a small net effect of -0.03 and -0.18 for women without land and women with land, respectively. Note, however, that, if there are shocks that take place later it becomes less likely that the mother will be able to fully compensate for the reduction in fertility.[36]

[36] Including the number of hurricanes a women has experienced between age 35 and 49 does not yield any statistically effect, mainly due to the relatively low number of women in this age group.

4.3 The Relation between Hurricanes and Mortality

As Section 2 discusses one possible explanation for the observed increase in fertility, at least among the households with land, from an higher risk of hurricanes could be an associated increase in mortality risk. While the fact that the results above are nearly identical between fertility and the number of children alive indicates that this is unlikely to be the complete story, it is worthwhile examining the possibility in more detail. The remainder of this section does that by estimating how mortality is affected by hurricane risk and the number of hurricanes experienced.

Given the lack of information on children who have died and those who have moved out of the household the data is not ideal for analysing mortality. The unit of analysis is the mother and not the child which would be more appropriate. Furthermore, given that the women are between 15 and 49 years old, their children can be anywhere between zero and 35 years old at the time of the survey. Out of the 6,648 women in the sample used to estimate the effect of risk on fertility 4,507 had one child or more and they form the basis for the analysis of mortality. Among the women with at least one child, 73 percent in households with land and 82 percent of those without land did not suffer the death of a child, while 15 and 10 percent had one death, and 6 and 4 percent experienced two deaths.

The two mortality outcomes of interest here are whether the woman has ever lost a child and the number of children who have died. The estimated equation is

$$M_i = \alpha + X_i'\beta + R_i'\gamma + S_i'\delta + \varepsilon_i, \qquad (7)$$

where M is the mortality outcome of interest, X is a vector of individual and household variables, R is a vector of risk, including interactions with individual and household variables and S measures shocks. The main difference from above is how the number of hurricanes is measured. Since a hurricane can increase mortality both directly and through its negative impact on income, it presumably affects all ages and not just the very young. The number of hurricanes is therefore the total number a woman has experienced from age 15 until age 49 or the survey date. The average number of hurricanes is 1.4 with a standard deviation of 0.8. Furthermore, the maximum number of hurricane shocks is 6, although less than two percent of the women have experienced more than 3 hurricanes. Alternative specifications of the number of hurricanes lead to qualitatively identical results, but often results in low precision.[37] Table 4 provides the descriptive statistics.

We estimate (7) using OLS with robust standard errors where the cluster level is the household.[38] The results are presented in Table 5. There are two different specifications for each of the two outcomes. All of the models use the number of hurricanes and the number of hurricanes interacted with owning land. Model I and III includes the annual risk of a hurricane in percent

[37]One possibility is to measure shocks as the number of hurricanes which have occured during a certain age periods of the mother, such as 15-19, 20-24, etc.

[38]The results using probit for the binary variable and tobit for the number of children are available on request.

Table 4: Descriptive Statistics — Mortality

Variable	Mean	Std. Dev.
Mortality dummy	0.2201	0.4144
Number of deaths	0.3745	0.8785
Age	31.9472	8.9445
$\text{Age}^2/100$	11.0061	5.8853
Indigenous	0.4540	0.4979
Owns land	0.4535	0.4979
Rural	0.6889	0.4630
Risk of hurricane (percent)	4.6455	0.9662
Risk of hurricane $\times$ owns land	2.1701	2.4448
Risk of hurricane $\times$ age	148.1643	52.0968
Risk of hurricane $\times$ age^2	50.9915	29.7668
Risk of hurricane $\times$ age $\times$ owns land	70.3926	84.6070
Risk of hurricane $\times$ age^2 $\times$ owns land	24.6575	34.0072
Hurricane shocks	1.3772	0.8120
Hurricane shocks $\times$ owns land	0.6488	0.9078

and the annual risk interacted with owning land while Model II and IV in addition also has age and age squared interacted with risk and interacted with owning land.

The main variables of interests are the two shock variables. For all models the interaction between the number of hurricanes and land ownership is positive and statistically significant, although the net effects are relatively small. One extra hurricane leads only to an increase of about two percentage point increase in the probability of having a child die. Looking at the number of children who have died an additional hurricane increases the number of dead children by less than 0.1 child.

There appear to be little effect of the number of hurricanes on the mortality of children born to women who live in households without land. All of

Table 5: Effects of Risks and Shocks on Mortality

	Probability of Mortality		Number of Deaths	
	Model I	Model II	Model III	Model IV
Age	0.0090*	−0.0036	−0.0096	0.0032
	(0.0054)	(0.0245)	(0.0134)	(0.0480)
Age squared / 100	0.0080	0.0213	0.0596**	0.0211
	(0.0093)	(0.0385)	(0.0240)	(0.0787)
Indigenous	0.1057***	0.1064***	0.2088***	0.2096***
	(0.0157)	(0.0157)	(0.0339)	(0.0341)
Owns land	0.0104	−0.0306	−0.1238	−0.1398
	(0.0726)	(0.0784)	(0.1432)	(0.1573)
Rural	0.0667***	0.0655***	0.1734***	0.1709***
	(0.0135)	(0.0134)	(0.0276)	(0.0275)
Hurricane risk (%)	0.0237	0.0252	0.0243	0.1038
	(0.0162)	(0.0784)	(0.0298)	(0.1483)
Risk × owns land	−0.0079	−0.1184***	−0.0085	−0.1656**
	(0.0147)	(0.0330)	(0.0291)	(0.0805)
Risk × age		−0.0012		−0.0084
		(0.0052)		(0.0107)
Risk × age squared		0.0035		0.0174
		(0.0083)		(0.0178)
Risk × age ×		0.0076***		0.0103*
owns land		(0.0022)		(0.0059)
Risk × age squared		−0.0123***		−0.0159
owns land		(0.0039)		(0.0106)
Hurricane shocks	−0.0274	−0.0469**	−0.0328	−0.0582
	(0.0170)	(0.0205)	(0.0406)	(0.0455)
Shocks × owns land	0.0333**	0.0669**	0.1124***	0.1380*
	(0.0164)	(0.0308)	(0.0435)	(0.0794)
Constant	−0.2697**	0.0095	−0.1450	−0.0932
	(0.1168)	(0.3758)	(0.2643)	(0.7015)
Observations	4507	4507	4507	4507
R-squared	0.12	0.13	0.14	0.14
Adj. R-squared	0.12	0.12	0.13	0.13
Log-Likelihood	−2127.79	−2121.64	−5483.02	−5478.59

NOTE: * significant at 10%; ** significant at 5%; *** significant at 1%
Robust standard errors in parentheses, clustered at the household level.
Additional variables (not shown) are department dummies
and a fourth-order polynomial in altitude.

the effects are negative and in Model II the effect is significant, which might appear counterintuitive. One possible explanation for this is as follows. First, women from households without land on average have lower fertility, which in itself should lead to lower mortality risk. Second, higher number of hurricanes means that it is more likely that a woman has experienced a hurricane shock before she begins childbearing. Since the results from above show that there is a negative effect of hurricanes on the number of children born, it may be that a women hit by a higher number of hurrricane both delay childbearing and end up with a lower number of children. Hence, the decrease mortality probability may be a result of this combination of a lower number of children from not having land combined with the possibility of delayed and reduced childbearing from a higher number of hurricanes.

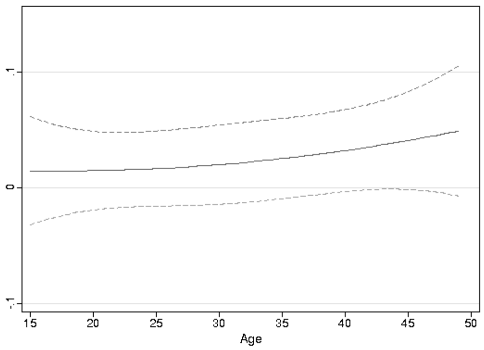
This explanation points to a problem with analysing mortality using this data set. Since we cannot follow individual children we do not know if a woman's children were even born when the hurricane hit. In essense we confound the fertility and the mortality effects of hurricanes, which may explain the relatively low effects on mortality.

Before discussing to what extent mortality can explain the positive marginal effect of hurricane risk on fertility it is worth looking at the effect of hurricane risk on mortality. Since higher risk leads to higher fertility we might also expect a higher mortality if less resources are devoted to each child as a result. This "second-order" effect has attracted some attention in the literature on child mortality in developing countries, although it generally has proven hard to identify (Wolpin 1997). In both Models I and III an increase in the risk of hurricanes leads to an increase in mortality, although the effect is not statistically significant and the effect is lower for households that own land than for those who do not.[39] Figure 3 show the marginal effect of risk by age for Models II and IV for both households without land and households with land. Interestingly, there appear to be little difference in how risk affect mortality between household with and households without land although the effect is generally positive for both. Somewhat contrary to expectations the households without land is closer to showing a statistically significant marginal effect of hurricane risk on mortality. In both the probability of mortality (Figure 3(a)) and the number of deaths (Figure 3(c)) the effect is statistically significant at the ten percent level for age 40 and above.

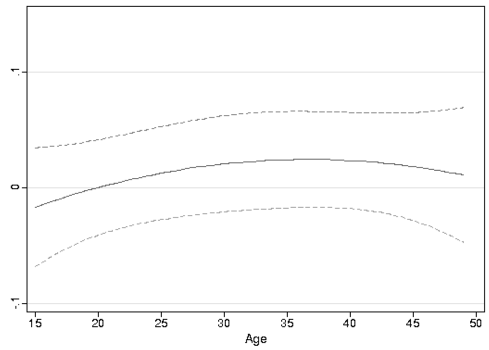
While we have shown that there is a positive relationship between the number of hurricane shocks and mortality, the effect is relatively small (although likely biased downward as discussed above). Furthermore, given that the effect of hurricane risk on the number of children alive is statistically significant and large it is unlikely that a mortality effect can explain more than a small part of the increase in fertility from increasing hurricane risk. For the sake of argument assume that a women in a high risk area can expect 3 hurricane over a period of time, which would be equal to a reduction in the number of surviving children of less than 0.3 for a household with land.[40] Even if this is significantly biased downward there is still a substantial gap to the increase in fertility that results from going from the lowest to the

[39]The closest to being statistically significant is the parameter on risk in Model I, where the p-value is 0.14.

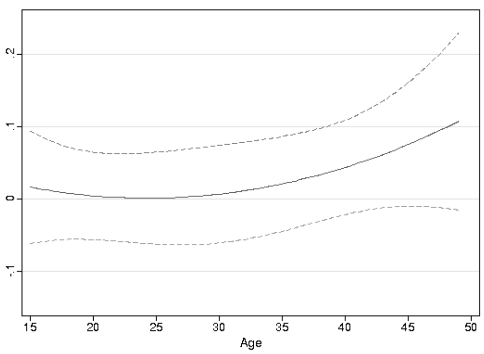
[40]For the highest risk area the time period would be equivalent to about 40 years.



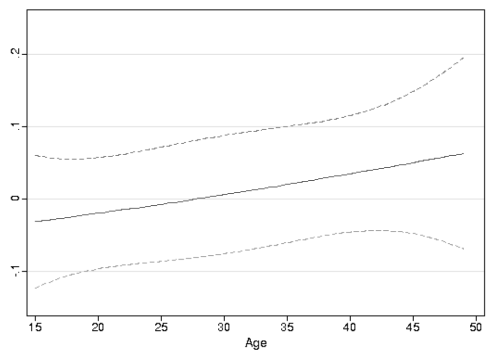
(a) Model II for Landless



(b) Model II for Land Owners



(c) Model IV for Landless



(d) Model IV for Land Owners

Figure 3: Marginal Effect of Hurricane Risk on Mortality

highest hurricane risk, which is about 1.2 children, especially since a woman in the lowest risk areas can still expect more than one hurricane during a 40 year period. We now turn to how hurricane risk affects investment in human capital.

5 Education, Risks and Shocks

This section presents results of the effects of hurricane risks and shocks on the educational attainment. We first discuss the econometric model and the selection of the sample. Second, we present the variables used and their expected effects. Third, the results are presented and discussed. Finally, we look at the return to education and how it interacts with the risk of hurricanes.

There is a number of different ways to specify educational attainment. Here we use the number of years of education, based on the highest grade and level reached.[41] The estimated equation is

$$E_i = \alpha + X_i'\beta + R_i'\gamma + S_i'\delta + \varepsilon_i, \tag{8}$$

where E is the years of schooling achieved, X is a vector of individual and household variables, R is a vector of risk, including interactions with individual and household variables and S measures shocks. We estimate (8) using OLS with robust standard errors where the cluster level is the household.

The sample used here is all adults aged 20 to 69 years of age, who are not born in a city or a town and who are not born in the Municipality of Guatemala (the capital and surrounding areas). This is the sample that corresponds best to the sample used in the fertility estimations above. Note

[41] Hence, repeat a year does not count as additional education. Alternative would be dummies such as "any schooling", "finished primary" etc., depending on the level of interest. Those results are available on request and lead to qualitatively identical results.

that selection is based strictly on place of birth, no where somebody currently resides, since this best captures the education decision for the originating households. If migration, of either an individual or a complete household, is an important response to hurricane risk and shocks then only looking at the population currently in the rural areas would bias the estimations. Since the sample of households is representative nationwide this way we will have something closely resembling a representative sample of educational attainment for the areas of interest.

The latter is the main reason why we do not use the information on the children born to the women in the sample. As mentioned above this is not the complete sample of children born, since the survey does not collect information on children who have either left the household or died. With a substantial migration it is likely that the education level of our sample will be different from that of the the true population. Furthermore, it is not clear a priori what the direction of the bias will be. On one hand, it is possible that those who are most exposed to risks and shocks are more likely to end school sooner and therefore leave the household. This would lead to an underestimation of the effects of risks and shocks, since we will be left with the part of the population that for one reason or another were better able to withstand, say, a shock. This could, for example, be children who have higher abilities and therefore are more likely to be kept in school by their parents.[42] On the other hand, it is possible that children from household

[42]See, however, Beegle, Dehejia, and Gatti (2004) for an example where it appears that

that can better withstand shocks are more likely to leave the household to go to a (better or higher level) school somewhere else. In that case we are left with a sample of children who are more likely to be affected by risks and shocks and therefore we might overestimate the effect. Beside the selection problem another issue is that a substantial number of children are still in school, which means that we would have to take account of right censoring; this is much less of a problem for the adult sample, although it is possible that some of the youngest adults are still enrolled. As is expected using the sample of children leads to results that are qualitatively similar to the ones we present below, but at a much lower level of significance.[43]

5.1 Variables

Table 6 presents the descriptive statistics for the variables used in estimating equation (8). As above the explanatory variables fall into three groups: Individual and household variables, risks and risk interactions and finally shocks, although the definitions for especially shocks are different from above. We discuss these after examining the dependent variable. The average education is relatively low at about 3.4 years and about 40 percent of the sample has no education at all. Just over 15 percent has more than a primary education (equal to six years of education), and less than 3 percent have more than a secondary education.

the opposite is the case. Those with lower abilities are more likely to go to school.

[43]The results for children are available upon request.

Table 6: Descriptive Statistics — Education

Variable	Mean	Std. Dev.
Education in years	3.3816	4.0986
Female	0.5268	0.4993
Age 30-39	0.2441	0.4296
Age 40-49	0.1925	0.3943
Age 50-59	0.1366	0.3435
Age 60-69	0.0862	0.2807
Indigenous	0.4453	0.4970
Owns land	0.2696	0.4438
Female × owns land	0.2265	0.4186
Risk of hurricane (percent)	4.5964	1.0086
Risk of hurricane × owns land	1.2431	2.1078
Risk of hurricane × female	2.4268	2.4148
Risk of hurricane × owns land × female	0.6171	1.6079
Hurricane shocks (age 0-6)	0.5392	0.7137
Hurricane shocks (age 0-6) × owns land	0.1456	0.4443
Hurricane shocks (age 0-6) × female	0.2848	0.5854
Hurricane shocks (age 0-6) × owns land × female	0.0721	0.3185
Hurricane shocks (age 7-12)	0.4025	0.6456
Hurricane shocks (age 7-12) × owns land	0.0972	0.3603
Hurricane shocks (age 7-12) × female	0.2164	0.5176
Hurricane shocks (age 7-12) × owns land × female	0.0506	0.2657

As above the main variables of interest are those that reflect the hurricane risk of an an area. This is again measured as the percent annual risk of experiencing a hurricane. Since people can move between areas a question is which municipality to base the risk measure on. First, for those who moved into their current municipality after turning 13 years old or older, we use the risk measure from the municipality they were born in. Second, if a person moved into their current municipality before turning 13 years old we use the risk measure from the current munipality. Finally, for those who are born in the area they are currently living in there is obviously no problems. The cutoff age of 13 is based on the approximate age when finishing primary education. Other cutoff ages leads to pratically identical results. As above the average annual risk of being hit by a hurricane is around 4.5, with a minimum of 3.4 and a maximum of 7.6. In addition to the interaction between risk and ownership of land there are now also two interactions with being female. First is the risk interacted with female and second is the interaction of being female with the interaction between risk and land ownership. These are included to capture possible different responses to risk by land ownership status and the sex of person.

Deciding on a measure of shocks is more complicated. We use two different measures of shocks. The first is the number of shocks that have occurred between the person's birth year and the year they turn six. The second is the number of shocks that have occurred between the year the child is supposed to begin school (at age seven) and their 13th year. One complication here is that the second shock measure is most likely to have an effect on individuals who were enrolled at the time of the shocks. For those who have never enrolled or have already left school before finishing primary the only effect of these shocks would be to decrease the chance of going back to school. Hence, we might expect less clear results from our analysis of the effects of shocks on education than on fertility. For the zero to six shock measure the average number of hurricanes is 0.5, while it is 0.4 for the seven to thirteen shock measure. In both cases the maximum number of hurricanes is four, although in both cases less than one percent were hit by more than two hurricanes.

As for risk we interact the two shock variables with a dummy for female and a dummy for land ownership and the complete interaction between all three.

Finally, the individual and households variable are mainly as above. The main differences are the we use five age dummies with being 20 to 29 years old is the excluded variable and that there now is a dummy for being female. Furthermore, we include the interaction between female and land ownership.

5.2 Results

The results for the determinants of education are presented in Table 7.[44] Five different specifications are presented. Model I does not include risk or shocks, while Model II adds the hurricane risk and the hurricane risk interacted with land. To allow for differences between boys and girls Model III interacts the risk variables with a dummy for being female. Model IV extends Model II with the two measures of hurricane shocks and the interaction with land ownership. Finally, Model V allows the effects of risk and shocks to vary by sex.

There is a statistically significant and substantial positive effect of hurricane risk on educational attainment for those without land in all models. This fits nicely with the negative effect of hurricane risk on fertility for this group. Presumably these households trade off the number of children against investments in human capital for their children. There are at least two possible explanations for this. First, returns to education might be higher in

[44]The results for the Tobit model are shown in Table 9.

Table 7: Effects of Risks and Shocks on Education — OLS

	Model I	Model II	Model III	Model IV	Model V
Female	−1.2848***	−1.2906***	−0.3353	−1.2914***	−0.2212
	(0.0563)	(0.0563)	(0.2970)	(0.0563)	(0.3008)
Age 30-39	−0.9277***	−0.9334***	−0.9416***	−0.5992***	−0.6038***
	(0.1052)	(0.1050)	(0.1046)	(0.1580)	(0.1572)
Age 40-49	−1.6217***	−1.6320***	−1.6068***	−1.4997***	−1.4718***
	(0.1081)	(0.1082)	(0.1079)	(0.1186)	(0.1183)
Age 50-59	−2.6294***	−2.6380***	−2.6246***	−2.5793***	−2.5576***
	(0.1031)	(0.1030)	(0.1027)	(0.1105)	(0.1101)
Age 60-69	−3.1861***	−3.1969***	−3.1776***	−3.2588***	−3.2245***
	(0.1141)	(0.1137)	(0.1137)	(0.1165)	(0.1165)
Indigenous	−2.4439***	−2.4205***	−2.2886***	−2.4194***	−2.2868***
	(0.1214)	(0.1211)	(0.1199)	(0.1211)	(0.1200)
Owns land	−0.1751**	0.7864*	0.9663**	0.8200**	1.0057**
	(0.0871)	(0.4135)	(0.4130)	(0.4132)	(0.4128)
Female × owns land			−0.9823***		−0.9877***
			(0.0967)		(0.0967)
Risk of hurricane (percent)		0.3180***	0.3846***	0.3554***	0.4072***
		(0.0955)	(0.1025)	(0.0966)	(0.1032)
Risk of hurricane × owns land		−0.2092**	−0.2493***	−0.2084**	−0.2189**
		(0.0865)	(0.0883)	(0.0871)	(0.0898)
Risk of hurricane × female			−0.1279**		−0.0991
			(0.0642)		(0.0648)
Risk of hurricane × owns land × female			0.0469		−0.0049
			(0.0291)		(0.0428)
Hurricane shocks (age 0-6)				−0.1513*	0.0146
				(0.0838)	(0.1079)
Hurricane shocks (age 0-6) × owns land				−0.1265	−0.3381**
				(0.1102)	(0.1607)
Hurricane shocks (age 0-6) × female					−0.2980**
					(0.1163)
Hurricane shocks (age 0-6) × owns land × female					0.3831*
					(0.2065)
Hurricane shocks (age 7-12)				−0.2408**	−0.1198
				(0.0963)	(0.1259)
Hurricane shocks (age 7-12) × owns land				0.0710	0.0058
				(0.1273)	(0.1989)
Hurricane shocks (age 7-12) × female					−0.2075*
					(0.1246)
Hurricane shocks (age 7-12) × owns land × female					0.0782
					(0.2440)
Constant	6.7444***	5.3900***	4.8355***	5.3087***	4.6856***
	(0.3518)	(0.5459)	(0.5722)	(0.5471)	(0.5739)
Observations	12331	12331	12331	12331	12331
R-squared	0.18	0.19	0.19	0.19	0.19
Adj. R-squared	0.18	0.18	0.19	0.18	0.19
Log-Likelihood	−33630.88	−33619.62	−33572.21	−33614.32	−33562.63
Risk + Risk × owns land = 0		1.04	1.46	1.86	2.74*
Risk + Risk × female = 0			6.85***		9.57***
Risk + Risk × land + Risk × female + Risk × land × female = 0			0.24		0.57

NOTE: * significant at 10%; ** significant at 5%; *** significant at 1%
Robust standard errors in parentheses, clustered at the household level.
Additional variables (not shown) are department dummies and a fourth-order polynomial in altitude.

areas that are more risk prone. We will return to this possibility below. Second, if migration as an insurance mechanism is important it may be more beneficial to families in higher risk areas to have fewer children and educate them more. Furthermore, while the effect of risk on education is lower for women and than for men this effect is not significant if shocks are included as in Model V. The total effect of increasing hurricane risk by one percentage point is equal to 0.4 years of school for men and 0.3 for women.[45]

The main result of interest is, however, how hurricane risks affect the schooling of individuals from households with land. While the estimated parameter for men is negative and statistically significant the total effect is 0.19, which is statistically significant different from zero![46] Hence, not only do households with land who live in more risk prone areas have more children, they also educated their boys more than households in less risky areas. Furthermore, while the effect might not appear large it should be kept in mind that the average educational attainment for men from households with land is just over 3 years. The difference between the highest and the lowest risk levels is about four percentage points, which would correspond to a difference in education of 0.8 years.

For girls in households with land the effect of increasing risk is not statistically significant. Note, however, that this is not because households with

[45]The latter is statistically different from zero at the one percent level.

[46]The F-statistics is 2.74, which is statistically significant at the 10 percent level with 6017 degress of freedom (recall that there is clustering at the household level). The result for the same hypothesis for the Tobit model yields a Chi-square statistics of 4.08, which is statistically significant at the five percent level.

land invest less in girls' education than those with land. The additional effect of being female in a household with land is very small, so most of the negative effect is common to households with and without land.

As for the households without land there are at least the same two possible explanations for the increase in both fertility and education with increasing risk of hurricanes as were mentioned above. In addition it is possible that landed household have a higher "internal" return to human capital. The argument for this follows the suggestion in Schultz (1975) that education might increase the ability to deal with disequilibria as was discussed in Section 2. One can imagine a situation in which a household needs both more people to help with post-hurricane reconstruction and need these people to be better trained to deal with the lack of resources which is likely after a hurricane. Without more detailed panel data it is, however, difficult to disentangle these different explanations.

The shocks that occurred before an individual begins school appear to have more of an impact than those that occur while the person is in school-going ages. While there is no statistically significant effect of hurricane shocks that occur between age 0 and 6 for men in household without land the effect is statistically significant and negative for women. Hardest hit is men from household with land, although the effect are relatively similar to the effect for women in household both with and without land. One hurricane shock has an estimated negative effect on years of schooling of 0.3. For the hurricanes that occur between age 7 and 12 there is little effect on men's schooling, no matter if they are from a household with land or without land. Women are, however, significantly negatively impacted with the largest negative impact for women from households without land.

While it is hard to distinguish between the migration and the ability to deal with disequalibria stories with the current data set we can examine how the return to education varies by hurricane risk. We do this by estimating a wage equation with years of education and risk of hurricanes and their interaction plus a standard set of other explanatory variables.[47] The sample consists of adults between 24 and 65 who live outside of the Municipality of Guatemala. The results are provided in Table 8. Model I shows the results without hurricane risk, while Model II includes hurricane risk and its interaction with years of education. Models III and IV are identically to Model II but are split by sex with males in III and females in IV.

What it clear is that it is unlikely that the higher education investment in boys for both household with and without land is due to higher returns to education in those areas. In fact, the contrary seems to be the case. As Model III shows there is a statistically significant negative effect of the interaction between hurricane risk and education. This is in line with both the story about human capital being less prone to destruction than physical capital leading to more investment in human capital *and* the possibility that higher

[47]Note, that these results are main explorative. There is no attempt to deal with questions of selection into wage labour or other issues, such as the return to education on own land. Furthermore, education is treated as exogenous, something which is obviously not correct given the results.

Table 8: Returns to Education and Hurricane Risks

	Model I	Model II	Model III	Model IV
Female	0.2696	0.2823		
	(0.2104)	(0.2105)		
Age	0.3613***	0.3599***	0.3601***	0.3751***
	(0.0676)	(0.0676)	(0.0814)	(0.1218)
Age squared /100	−0.3680***	−0.3661***	−0.3560***	−0.4059***
	(0.0830)	(0.0830)	(0.0998)	(0.1500)
Indigenous	−0.3803*	−0.4118**	−0.3933*	−0.3224
	(0.1945)	(0.1951)	(0.2338)	(0.3552)
Rural	−0.6095***	−0.6212***	−0.5884***	−0.5891**
	(0.1663)	(0.1664)	(0.2041)	(0.2892)
Education (years)	0.8027***	0.9178***	0.9990***	0.6571***
	(0.0212)	(0.0678)	(0.0855)	(0.1063)
Education × Female	−0.1541***	−0.1562***		
	(0.0307)	(0.0307)		
Hurricane Risk (%)		−0.0266	0.1804	−0.4079
		(0.1780)	(0.2154)	(0.3250)
Risk × education		−0.0246*	−0.0420**	−0.0006
		(0.0138)	(0.0177)	(0.0223)
Constant	−3.6155**	−3.5591**	−4.4896**	−1.5716
	(1.4537)	(1.6705)	(2.0000)	(3.0762)
Observations	6561	6561	4321	2240
R-squared	0.31	0.31	0.34	0.27
Adj. R-squared	0.31	0.31	0.34	0.26
Log-Likelihood	−20771.46	−20769.44	−13620.75	−7124.03

NOTE: * significant at 10%; ** significant at 5%; *** significant at 1%
Additional variables (not shown) are department dummies and a fourth-order polynomial in altitude.

education leads to individuals being better at dealing with shocks.

6 Conclusion

With risk being a significant factor in developing countries it is important to analyse what the effects of risk are on households' decisions. Two areas that are especially important are education and fertility since these have a substantial impact both on individuals' welfare and on a country's growth prospects. However, a reoccuring problem in the literature on risk coping is that while data on shocks are often available, it is significantly harder to capture risks.

This paper uses unique data on hurricanes in Guatemala over the last 120 years, which can be used to measure both risk *and* shocks, combined with a household survey to analyse how decisions on fertility and education respond to both risk and shocks For households with land an increase in the *risk* of hurricanes lead to both higher fertility and higher education, while households without land have fewer children but also higher education. Hurricane *shocks* lead to decreases in both fertility and education, although there is a substantial compensatory effect on fertility later in life.

While a number of possible explanation can be advanced to explain this interesting pattern it is most likely that a combination of direct insurance through having more children and insurance through migration that explains the higher number of children for households with land. That education is also increasing in risk is especially fascinating and even more so since fertility also increases for the households with land. This increase can be attributed to both the increased ability to deal with disequilbria and the increased opportunities if a person migrates.

One cave-at with this research is that we are looking only at one specific risk, namely hurricanes. This is important given, as argued in the paper, that children or family more general might play a special role in the aftermath of hurricanes that cannot be fulfilled by the labour market. Hence, one worthwhile direction for future research would be to look at how other types of risks affects these same behaviours. Furthermore, it is possible to use the hurricane data to look at other decisions, such as crop choice or the decision to migrate

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A Appendix

Table 9: Effects of Risks and Shocks on Education — Tobit

	Model I	Model II	Model III	Model IV	Model V
Female	−2.4387***	−2.4474***	−0.1537	−2.4482***	−0.0315
	(0.0911)	(0.0911)	(0.4346)	(0.0910)	(0.4397)
Age 30-39	−1.5077***	−1.5180***	−1.5367***	−0.9517***	−0.9670***
	(0.1480)	(0.1478)	(0.1471)	(0.2346)	(0.2326)
Age 40-49	−2.7509***	−2.7670***	−2.7256***	−2.5440***	−2.4979***
	(0.1627)	(0.1628)	(0.1622)	(0.1793)	(0.1784)
Age 50-59	−4.9154***	−4.9269***	−4.9084***	−4.8041***	−4.7780***
	(0.1868)	(0.1864)	(0.1856)	(0.1959)	(0.1946)
Age 60-69	−6.2405***	−6.2626***	−6.2301***	−6.3486***	−6.2918***
	(0.2446)	(0.2438)	(0.2437)	(0.2455)	(0.2452)
Indigenous	−4.0813***	−4.0459***	−3.7953***	−4.0448***	−3.7950***
	(0.1916)	(0.1910)	(0.1890)	(0.1909)	(0.1889)
Owns land	−0.1034	1.3506**	1.7575***	1.4280**	1.8484***
	(0.1395)	(0.6162)	(0.6158)	(0.6172)	(0.6168)
Female × owns land			−1.9951***		−1.9971***
			(0.1784)		(0.1785)
Risk of hurricane (percent)		0.4685***	0.6424***	0.5311***	0.6906***
		(0.1305)	(0.1377)	(0.1328)	(0.1396)
Risk of hurricane × owns land		−0.3181**	−0.3953***	−0.3179**	−0.3591***
		(0.1318)	(0.1332)	(0.1325)	(0.1352)
Risk of hurricane × female			−0.3445***		−0.3166***
			(0.0938)		(0.0953)
Risk of hurricane × owns land × female			0.0700		0.0084
			(0.0478)		(0.0701)
Hurricane shocks (age 0-6)				−0.2300*	−0.1073
				(0.1189)	(0.1453)
Hurricane shocks (age 0-6) × owns land				−0.1875	−0.4742**
				(0.1701)	(0.2229)
Hurricane shocks (age 0-6) × female					−0.2225
					(0.1689)
Hurricane shocks (age 0-6) × owns land × female					0.5349*
					(0.3169)
Hurricane shocks (age 7-12)				−0.4068***	−0.2291
				(0.1487)	(0.1795)
Hurricane shocks (age 7-12) × owns land				0.0487	0.0211
				(0.1988)	(0.2748)
Hurricane shocks (age 7-12) × female					−0.3050
					(0.1881)
Hurricane shocks (age 7-12) × owns land × female					−0.0733
					(0.3807)
Constant	7.1775***	5.1476***	3.9159***	4.9989***	3.6904***
	(0.5462)	(0.8104)	(0.8318)	(0.8126)	(0.8341)
Observations	12331	12331	12331	12331	12331
Log-Likelihood	−26172.67	−26162.19	−26087.61	−26156.79	−26078.95

Note: * significant at 10%; ** significant at 5%; *** significant at 1%
Robust standard errors in parentheses, clustered at the household level.
Additional variables (not shown) are department dummies and a fourth-order polynomial in altitude.