The Effects of Natural Disasters on Human Capital Accumulation

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Abstract

In this paper I investigate the effects of disasters on human capital accumulation using an extensive panel dataset on natural disasters, covering 170 countries over a 25 year period (1980-2004). My analysis shows that disasters have both a direct, contemporaneous effect and a long-term, indirect effect on human capital. While the direct effects - primarily related to injury, illness and death suffered as a result of the disaster - are relatively straightforward, the indirect effects will depend on household decision-making in the aftermath of the disaster. Treating human capital as a long-term investment decision, it is clear that access to finance is likely to be a crucial factor in household decisions about whether or not to invest in children's health and education. Indeed, my results show that aid flows are effective in mitigating the long-term impacts of disasters on health outcomes. However, for school enrollment rates, the longer-term effects of disasters are dependent on the availability of credit. These findings could have important policy implications. The indirect effects are unlikely to have been identified in previous analyses that focus on the short-term impacts of natural disasters. Given the importance of human capital in the process of economic development, the results presented here suggest that natural disasters represent a significant threat to the development prospects of relatively poor countries.

Keywords: *natural disasters, epidemics, human capital, credit markets, development*

JEL Classification: *O11; O15; Q54; Q56*

1 Introduction

In this paper I investigate the effects of natural disaster events on the accumulation of human capital, with a particular focus on the circumstances of low-income countries. Natural disasters represent transient shocks to the economy, and therefore in theory, should be relatively unimportant for the long-term process of economic development. However, in previous research Frank Barry, Richard Tol and I (McDermott *et al.* , 2011) have shown that in the context of developing countries, with weak financial sector development, disaster recovery will be delayed by a lack of access to credit, resulting in persistent medium-term effects of disasters on economic growth.

Natural disasters frequently result in large-scale loss of life, injury and the spread of illness - alongside the displacement of populations, the disruption to everyday life and the welfare costs imposed by the associated destruction of physical assets. These humanitarian effects of natural disasters are suffered disproportionately by poorer people and countries. Potentially, the disruption of human capital could represent an important channel of transmission from the transient shock of a disaster to long-term economic development.

Human capital accumulation has come to be seen as a crucial determinant of long-term growth potential (e.g. Barro, 1991). Quite apart from this indirect link from human capital to development (as proxied by economic growth), the accumulation of human capital - unlike the expansion of GDP - surely represents a development goal in itself. The term human capital generally refers to the health and education of a population. It thus forms two thirds of the UN's Human Development Index, which is made up of income per capita, life expectancy and education.

In spite of its potential significance, relatively few studies have attempted to test the effects of natural disasters on human capital accumulation at a macro level (i.e. using national level data). One exception to this is a recent paper by Crespo Cuaresma (2010), which finds evidence of a negative correlation between geological disasters and secondary school enrollment rates. At a micro level (using household level data and/or detailed case studies) there is a range of literature that examines the effects of shocks due to natural disaster events on household consumption, investment and human capital accumulation (e.g. Dercon, 2004; Jalan & Ravallion, 2001; Lokshin & Ravallion, 2000). With regard to human capital accumulation, a recent review of this micro literature is provided by Baez *et al.* (2010).

In general, the long-term economic effects of natural disasters are as yet not well understood (Cavallo & Noy, 2009). One of the few papers that attempts to quantify the long-term consequences of disasters on economic growth is a much-cited paper by Skidmore & Toya (2002). These authors find a positive correlation between disaster frequency and economic growth, arguing that this could be the result of disasters lowering the opportunity cost of investing in human capital (relative to investing in physical capital).[1] However, their findings have been questioned on methodological grounds (Raddatz, 2009). Their theory regarding the relative investment in human as opposed to physical capital remains an untested hypothesis. In this paper I set out to test the effects of disasters on human capital accumulation.

1.1 The Humanitarian Effects of Natural Disasters

Natural disaster events can have devastating impacts on the populations of affected regions. However, the economic consequences of humanitarian disasters are not clear *a priori*. It is not generally thought, for example, that changes in the absolute size of the population should affect the rate of economic growth. This relationship may become more complex if natural disasters affect certain age-groups disproportionately, thus altering the demographic profile of the population - something which has been shown to influence economic growth (Bloom *et al.* , 2001).

The human consequences of disasters may be significant for economic growth through their effects on human capital accumulation, which has come to be seen as a crucial determinant of long run development potential in the so-called new economic geography

[1]It is highly debatable to what extent the physical capital effects of disasters outweigh the human capital effects, as will become apparent from the discussion below.

literature (Sachs *et al.* , 2001; Masters & McMillan, 2001), and in modern theories of economic growth (Mankiw *et al.* , 1992).

The accumulation of human capital is likely to be affected by extreme events in two ways; directly - through a combination of injury, illness and death - and indirectly, through the effects of these events on household income and time budgets. The direct effects are quite straightforward. Illness and injury associated with extreme events prevent children from attending school, while those killed by extreme events represent a lost investment in human capital. Furthermore, natural disaster events often lead to disease outbreaks, predominantly in poorer countries where infrastructure may be inadequate.

Hales *et al.* (2003) detail the potential impacts of extreme weather events (and other natural/humanitarian disasters) on the disease profile of the human population. In particular, extremes of both flooding and drought have been associated with increased incidences of malaria, outbreaks of various water-borne diseases (including cholera, typhoid and other diarrhoeal diseases) and rodent-borne diseases such as plague, Lyme disease and hantavirus pulmonary syndrome (HPS).[2]

While disease epidemics are generally the result of a complex interaction between physical, ecological and social mechanisms, the trigger is often an extreme weather event, leading to; shortage or contamination of water supplies; malnutrition of the population (through reduced food supply) and population displacement; increased pressure on local infrastructure and health facilities; and in some cases improved breeding conditions for the vector organisms and intermediate hosts that carry disease (Hales *et al.* , 2003). The effects of disease on human capital accumulation are unsurprisingly profound, and include; missed school days due to illness, the loss of past investments through death, and in some cases permanently reduced cognitive ability as a result of contracting certain diseases.

[2]There is also a significant literature on the mental health impacts of disasters, as reviewed in Norris *et al.* (2002). Various conditions such as post-traumatic stress disorder (PTSD), depression and anxiety are commonly found amongst populations that have experienced and survived disasters. The review by Norris *et al.* (2002) shows that the severity of mental health impacts is found to be higher for disasters occurring in developing as opposed to developed countries. However, the review also concludes that "man-made" disasters, especially mass violence events, tend to have a greater impact on mental health of the surviving population than "natural" disasters.

In a recent study, Eppig *et al.* (2010) show a strong negative correlation between parasite prevalence and average national IQ scores. These authors argue that various diseases retard brain development due to the extra strain they place on the body's metabolic capacity. A similar view is put forward by Sachs & Malaney (2002) in their review of the developmental effects of malaria.

The indirect impacts of disasters for human capital are again likely to be much more significant in poorer countries. By definition, natural disasters represent a negative wealth shock. Disasters also frequently affect the time available for labour force participation. For example, people's lives may be disrupted by damage to basic infrastructure and utilities, while family members may become ill, or get injured or killed by the event, reducing available time at the household level. Where people live close to subsistence, a negative shock to household income or a reduction of available time could have profound effects on household budget decisions - e.g. decisions regarding the education of children. Poorer households in developing countries will often be forced to withdraw children from school in response to a shock to household income (Jacoby & Skoufias, 1997). In this way a transient shock due to the occurrence of a natural disaster might have a lasting legacy for economic development.

1.2 Human Capital and Credit Access

It has often been shown that educational attainment depends, at least partially, on parental income. A range of studies based on US data are reviewed by Taubman (1989). A more recent discussion of the relationship between credit constraints and human capital is provided by Lochner & Monge-Naranjo (2011). While such a positive correlation could be explained by the consumption good interpretation of education, it may also be a result of liquidity constraints on investment in human capital. In the context of low-income countries, the liquidity constraint interpretation seems the more plausible, while supporting evidence is presented in Jacoby (1994) for Peruvian data.

Credit markets for investing in human capital are unlikely to function well, for a number of reasons (Loury, 1981; Becker & Tomes, 1979). Parents cannot constrain their children to repay debts incurred on their behalf; the likely returns to education are unknown, even to the borrower; while factors such as childhood nutrition and pre-school education are fundamentally income-constrained. Jacoby & Skoufias (1997) find that school attendance in rural Indian villages responds to income shocks, which they interpret as evidence of incomplete markets for investing in human capital. Poorer households are known to "self-insure" against income shocks by drawing on child labour in times of scarcity (Scoones & Chibudu, 1996). Further evidence of the link between income volatility and investment in human capital is presented in Flug *et al.* (1998). As a consequence, transient shocks can have long-run effects on growth through the mechanism of reduced investment in human capital accumulation.

2 Modelling the Human Capital Effects of Extreme Events

In this section I present the theoretical framework for my analysis. A simple two-period model is used to demonstrate the effects of natural disasters on the optimal allocation of household time between labour force participation and human capital accumulation, as follows:[3]

Agents maximize utility

$$U = ln(C_1) + Bln(C_2) \tag{1}$$

subject to

$$C_1 = F(HK_1, L_1) - S_1 \tag{2}$$

and

$$C_2 = F(HK_2, L_2) + \frac{S_1}{R} \tag{3}$$

where periods are subscripted 1 and 2. The production function F(•, •) is assumed to be at least twice continuously differentiable and exhibit constant returns to scale in its two arguments. B is the discount factor and R is the interest factor (i.e. one over one

[3]The basic structure of the model follows Barry (1999) and McDermott *et al.* (2011).

plus the interest rate). For the unconstrained small open economy, the interest rate is an exogenous, risk-free world interest rate. S_1 represents savings in the first period - i.e. the difference between income and consumption.

For simplicity, the accumulation of human capital is assumed to depend solely on time spent acquiring productive skills. Thus human capital accumulation is through foregone labour. Agents are endowed with a stock of productive skills in period one, which they supplement by spending time training during the first period.[4]

$$HK_2 = HK_1 + h \tag{4}$$

A further constraint on maximization behaviour is time. In period 1 agents must allocate their time between working and human capital accumulation. It is assumed that human capital must be accumulated one period in advance of use, and therefore no time is spent accumulating human capital in period 2.

$$T_1 = L_1 + h \tag{5}$$

$$T_2 = L_2 \tag{6}$$

Where L_i represents the fraction of time devoted to labour force participation in each period, and h the fraction of time devoted to human capital accumulation in period 1.

Thus, using equations (5) and (6) we can write HK_2 as follows

$$HK_2 = HK_1 + T_1 - L_1 \tag{7}$$

Replacing HK_2 in equation (3) with this new expression, we now have

[4]An alternative way of thinking about this trade off between labour force participation and human capital accumulation, is a parent's decision about how to divide their time between working and caring for or educating their children. This interpretation is similar in spirit to the idea of the "quantity-quality trade off" (see Becker *et al.* , 1990).

$$C_2 = F[(HK_1 + T_1 - L_1), L_2] + \frac{S_1}{R} \tag{8}$$

The first-order conditions for the solution of the maximization problem are thus

$$C_2 = C_1 \left(\frac{B}{R}\right) \tag{9}$$

$$F_{HK2} = F_{L1}/R \tag{10}$$

Equations (9) and (10) represent the inter-temporal efficiency conditions for effective consumption and investment. Optimal investment in human capital involves equating the return on human capital (the marginal product of human capital in period 2, F_{HK2}) with the returns to labour force participation, scaled by the interest rate. Optimal consumption involves consumption smoothing according to (9).

Shocks that cause disruptions to people's lives and/or cause injury, illness or even death, can be modelled as a reduction in available time in period 1. From (9) above, we know that in equilibrium $C_2 = C_1(B/R)$. We can use (2) and (8) to rewrite this expression as follows

$$\left(\frac{B}{R}\right)[F(HK_1, L_1 - S_1] - F[(HK_1 + T_1 - L_1), L_2] + \frac{S_1}{R} = 0 \tag{11}$$

This expression (which we denote by Φ) allows us to exploit the implicit function theorem in solving the model. We need to verify first that $\Phi_{L1} \neq 0$ and that $\Phi_h \neq 0$. Recalling that $HK_2 = HK_1 + T_1 - L_1$ we have

$$\Phi_{L1} = (B/R)F_{L1} + F_{HK2} > 0 \tag{12}$$

Similarly, rewriting L_1 as $(T_1 - h)$ and HK_2 as $(HK_1 + h)$ we have

$$\Phi_h = -F_{L1}(B/R) - F_{HK2} < 0 \tag{13}$$

For a shock to available time (occurring in period 1), the comparative statics we are interested in are (dL_1/dT_1) and (dh/dT_1). By the implicit function theorem

$$(dL_1/dT_1) = (-\Phi_{T1}/\Phi_{L1}) = ([F_{HK2} - (B/R)F_{L1}]/\Phi_{L1}) \tag{14}$$

Since we know that the denominator is positive, the sign of equation (14) depends on the relative magnitudes of F_{HK2} and F_{L1}.

Similarly,

$$(dh/dT_1) = (-\Phi_{T1}/\Phi_h) = ([F_{HK2} - (B/R)F_{L1}]/\Phi_h) \tag{15}$$

In this case the denominator is negative.

From the first-order condition for optimal 'investment' (i.e. optimal accumulation of human capital), we know that $F_{HK2} = F_{L1}/R$. Thus it must be that, in equilibrium, $F_{HK2} > F_{L1}(B/R)$, (given that $0 < B < 1$). The results of the implicit function theorem analysis therefore imply that

$$(dL_1/dT_1) > 0 \tag{16}$$

and

$$(dh/dT_1) < 0 \tag{17}$$

or in other words, as T_1 falls, the fraction of available time devoted to labour force participation (L_1) falls, while the fraction of available time devoted to human capital accumulation (h) rises (in order to maintain the optimal *level* of investment in human capital).

For the unconstrained economy, the reallocation of time following the shock in period 1 will serve to maintain the optimal level of investment in human capital. As available time shrinks in period 1 (as a consequence of the shock), unconstrained agents will devote a greater proportion of their time to human capital accumulation in order to maintain the optimal (equilibrium) investment level; i.e. in order to maintain $F_{HK2} = F_{L1}/R$.[5] In this way, the shock is fully compensated for, in terms of its effects on human capital

[5]This assumes diminishing marginal returns to human capital investment.

accumulation.

However, the shock to available time is not costless, even for the unconstrained economy. Combining (2), (8) and (9) we can write an equilibrium expression for C_1 as follows

$$C_1 = \frac{R}{(B+1)} \left\{ F[(HK_1 + T_1 - L_1), L_2] + \left(\frac{1}{R}\right) F(HK_1, L_1) \right\} \tag{18}$$

For a shock that reduces available time in period 1, totally differentiating this equation yields

$$\frac{dC_1}{dT_1} = \frac{R}{(B+1)} \left[F_{HK2} + \left(\frac{1}{R}\right) F_{L1} \right] > 0 \tag{19}$$

indicating, as one would expect, that such a shock will force a reduction in consumption. By the first-order condition for optimal consumption (equation 9), second period consumption must also fall as follows:

$$\frac{dC_2}{dT_1} = \frac{B}{(B+1)} \left[F_{HK2} + \left(\frac{1}{R}\right) F_{L1} \right] > 0 \tag{20}$$

Thus, the shock to available time causes consumption to fall in each period, reducing lifetime welfare.[6] For relatively poor households, a drop in consumption may involve the reduction of calorie intake leading to malnutrition, or the inability to afford medicines and basic health services. Thus, for households living close to subsistence, these welfare effects of the disaster shock will not only reduce utility in the short run (by forcing a reduction in consumption), but may also have longer-term effects on the productivity of the household, if a reduction in consumption leads to worse health outcomes.[7]

In a credit-constrained economy, with no access to world capital markets, the interest rate is no longer an exogenous world rate, but rather an endogenously determined rate (that serves to clear the goods market in each period). For a shock that reduces available resources in the economy (e.g. household time) in period 1, the interest rate will rise to

[6] For a credit-constrained economy, optimal consumption smoothing may not be possible, with the result that the burden of these welfare effects would be absorbed primarily by reduced first period consumption.

[7] Zimmerman & Carter (2003) discuss the potential for consumption shocks to translate into productivity shocks for households living close to the subsistence threshold.

preserve equilibrium. A higher interest rate means the interest factor, R, is smaller, and therefore implies a higher required rate of return on human capital investments (given $F_{HK2} = F_{L1}/R$ in equilibrium). Assuming diminishing marginal returns to human capital accumulation, a rising interest rate will imply a lower level of investment in human capital. Thus, the reallocation of time in period 1 following the shock, will not maintain investment in human capital at pre-shock levels in a credit-constrained economy.

To see this effect, we need to return to the results obtained above for (dL_1/dT_1) and (dh/dT_1). The sign of these partial derivatives depends on the relative values of F_{HK2} and $F_{L1}(B/R)$. With a constant R, we know that $F_{HK2} > F_{L1}(B/R)$ (from the first-order condition for optimal investment). However, if the interest rate rises in response to the shock, and thus the interest factor (R) falls, the magnitude of this inequality is diminished. The partial derivatives are thus necessarily smaller in magnitude, meaning that the compensating reallocation of time is dampened in the credit-constrained economy.

3 Empirical Analysis

Based on the literature review of the humanitarian effects of natural disasters, we would expect that disasters would have significant direct (contemporaneous) effects on human capital accumulation. However, I have also shown - using evidence from the literature on human capital investment and some simple theoretical analysis - that disasters are likely to have additional indirect (dynamic or lagged) effects on households' ability to invest in human capital. In this section, I test these ideas on a panel of data covering 170 countries over the period 1980-2004.

3.1 Data

Data on natural disasters are obtained from EM-DAT, the international emergency events database maintained by the Centre for Research on the Epidemiology of Disasters (CRED) at the University of Louvain in Belgium. This dataset covers all major natural disaster events across 180 countries from 1960 to the present. Economic data are taken from the

World Bank's World Development Indicators 2010. As a measure of the flow of investment in education, I use secondary school enrollment rates - defined as the ratio of total enrollment, regardless of age, to the population of the age group that officially corresponds to secondary level education in each country. According to the World Bank, "secondary education completes the provision of basic education ... and aims at laying the foundations for lifelong learning and human development".[8] I also investigate the effects of disasters on various measures of health outcomes - life expectancy (aggregate, and separately for males and females), and maternal, infant and under-five mortality rates. Unfortunately the data on these human capital indicators are not available on an annual basis for most countries. Because of this data restriction, I decided to aggregate the available data into 5-year periods. The data sample covers the period 1980-2004, thus resulting in 5 periods of 5 years each.

I construct three measures of disasters, aggregated over the 5-year periods, for use in my analysis. It is standard in the literature on the economic effects of natural disasters to take the proportion of a country's population affected by disasters as a measure of the disaster's severity. This method avoids using the controversial economic damages data, and also makes sense in the present context, given the focus on the humanitarian effects of disasters.

In a previous paper (McDermott *et al.* , 2011), Frank Barry, Richard Tol and I constructed a measure of disaster severity using annual data as follows:

$$Disaster_{it} = \Sigma_j \frac{TotalAffected_{it,j}}{Population_{i,t-1}} \tag{21}$$

where j indexes the number of events recorded in country i in year t.[9] I use this as the basis for the three measures of disasters included in my analysis here.

The first measure I construct is a count of the number of years (in each 5-year period)

[8]See the World Bank's online database of World Development Indicators: http://data.worldbank.org/indicator/SE.SEC.ENRR.

[9]The total number affected by a disaster includes those injured, made homeless or otherwise displaced by the event. The population from the previous period (*t-1*) is taken to avoid the denominator being dependent on the numerator in the equation for $Disaster_{it}$.

in which the above ratio exceeds 0.5 percent of the population. This measure is therefore restricted to be an integer between 0 and 5 in each country-period observation. The second measure of disaster severity that I construct is a simple sum of the above ratio over each 5-year period. Finally, I construct a binary measure of disaster severity that takes a 1 if the sum measure for the 5-year period exceeds 2.5 percent of the population, and a 0 otherwise.

I use the level of credit to the private sector as a proportion of GDP (as originally compiled by Levine *et al.* (2000)) as a proxy for financial sector development. The data for this series are taken from the Wold Bank's World Development Indicators.[10] I am also interested in the role of aid flows, and their potential to mitigate the humanitarian effects of disasters. I use the net Official Development Assistance (in current US$ per capita) series form the World Bank's World Development Indicators, as my measure of aid flows. Summary statistics for the key variables used in my analysis are included in table 1.

3.2 Empirical Framework

In the empirical analysis, reported below, I run panel regressions of the following form

$$HK_{it} = \beta_0 + \beta_1 y_{it} + \beta_2 D_{it} + \beta_3 credit_{it} + \beta_4 ODA_{it} + \beta_5 D_{it} * X_{it} + \theta_i + \theta_t + \epsilon_{it} \quad (22)$$

where HK_{it} represents the relevant human capital measure in country i for period t. The term D_{it} represents the various measures of natural disasters described above. I use an interaction term $D_{it} * X_{it}$ - where X is either credit or aid flows, depending on the regression specification - in order to test directly the potentially mitigating influence of credit access or aid flows on the relationship between disasters and human capital.

In most of the reported regressions, I include income per capita in logs (y_{it}), credit and aid flows (ODA) as additional, separate control variables. To control for any omitted country-specific, time-invariant factors, I also include country fixed effects (θ_i) and cluster errors by country. I also include time fixed effects (θ_t) to control for trends in the data

[10] This data series is discussed in more detail in McDermott *et al.* (2011).

or shocks that affect all regions simultaneously. We would expect the period fixed effects to pick up the general trend towards higher educational attainment and better health outcomes over time, although this approach should also control for any common shocks occurring across countries in a given period, that are not otherwise controlled for in my regressions.

To test for the indirect (dynamic) effects of disasters on human capital accumulation - as discussed above - I run versions of the above regression with lags of the disaster term and the interaction term added. If the cumulative coefficients on the sum of the contemporaneous and lagged variables remains significant, we can interpret this as evidence that disasters have *persistent* effects on human capital accumulation. Indeed, my results show that the cumulative coefficients remain significant with two lags added, indicating persistence in the disaster effects on human capital. These results form the most important contribution of the paper, as they indicate an indirect mechanism of effect from disasters to human capital, and potentially important long-term effects of disasters on development that would not be identified in more standard short-term analyses of disaster impacts.

3.3 Results

I present the results of my regression analysis in tables 2 - 13. While the results vary somewhat (in terms of significance) across the different model specifications, there appears to be sufficient evidence to support the notion that disasters have both direct and indirect effects on human capital. The direction of the effects is as expected and consistent across different model specifications (and measures of disasters), with disasters reducing school enrollment rates and life expectancy and raising mortality rates for mothers, infants and under-5s.

In general the magnitude (and significance) of the effects appears to be greater for poor countries than for the full sample of countries (the one exception being the contemporaneous effect of disasters on school enrollment - tables 2 and 3). Disasters also appear to have a stronger effect on life expectancy for females than for males. This is true for both the contemporaneous effects and the lagged (indirect) effects. This finding is suggestive of a gender-based aspect to the impacts - perhaps reflecting greater ex-ante vulnerability of females, or indeed an imbalance in the allocation of post-disaster resources.

It is interesting to note that income measures appear to be important for health outcomes, whereas for school enrollment rates, credit access appears to matter more. For the contemporaneous results, we see evidence of this distinction in the coefficients on income per capita, ODA and the credit measure and also in the interaction terms between disasters and credit and between disasters and ODA. This relationship is also borne out in the dynamic or lagged analysis, which shows that disasters have persistent effects on human capital at up to 15 years after the event. These effects are mitigated, in the case of school enrollment rates, by access to credit, whereas aid flows appear to be effective in mitigating the longer-term effects of disasters on health outcomes.[11]

4 Discussion

The reported results show that disasters have important consequences for human capital accumulation. Human capital clearly represents a goal of development, in itself. But it is also a key ingredient in building sustainable economic development in poor countries. The direct effects of natural disasters on human capital are quite straightforward, resulting from a combination of injury, illness and death caused by the disaster. The direct (contemporaneous) results are therefore unsurprising, although such effects have rarely been demonstrated at a macro level in previous literature. The indirect effects - which operate through the effects of disasters on household time and budgeting decisions - have also been shown here to be substantial. Such effects, in the case of school enrollment rates, appear to be dependent on the ability of households to access finance in the immediate aftermath of a natural disaster. For the health outcomes, the indirect effects of disasters appear to be mitigated by aid flows.

[11] For school enrollment rates, the interaction between disasters and ODA was not significant in the lagged regressions. Similarly, for the health outcomes, the interaction between disasters and credit access was not significant in the lagged regressions.

The dynamic results pick up on effects that would not otherwise be revealed in the analysis. The occurrence of a natural disaster might impact on the health and wellbeing of young children and infants (and on the financial circumstances of their families). Such effects (other than fatalities of course) might be considered transitory in nature. However, this is only the case provided the family has access to the finance necessary to seek medical treatment and pay for medicines (in the case of injury or illness) or to keep their children in school even in the face of a negative shock to household wealth (including the loss of household assets and income or a reduction in available time). If such finance is unavailable to the household at the time of the disaster, the transient shock may have long lasting effects on the ability of the household to invest in education. Illness and malnutrition in early childhood have been shown to have dramatic long-term effects on human capital accumulation (e.g. Alderman *et al.* , 2006; Lozoff, 1989; McKay *et al.* , 1978), while of course a child that is withdrawn from school at primary level is unlikely to go on to secondary education. These effects would only show up in the secondary school enrollment data once the child has reached the age at which secondary school attendance normally begins. This might be some 10 or more years after the disaster - thus justifying the inclusion of two lags in the dynamic analysis.[12] Analyses that focus on the short-term impacts of disasters are likely to miss the potentially important indirect human capital effects identified here.

5 Conclusions

While it is obvious - and well documented - that natural disasters can have large-scale humanitarian effects, the implications of such effects for the accumulation of human capital have rarely been demonstrated at a macro level. It has also been pointed out recently that our understanding of the long-term economic effects of natural disasters remains relatively limited. This paper contributes to the literature by demonstrating both a direct (contem-

[12]The dynamic analysis covers a total period of between 10 and 15 years after the disaster, given that the disaster could have occurred at any stage during the contemporaneous 5-year period, and the analysis includes a further two 5-year periods.

poraneous) and an indirect (dynamic) effect of disasters on human capital accumulation at a macro level. The dynamic effect is particularly noteworthy, as it indicates the potential for disasters to have long-term impacts on the development prospects of affected regions - effects which would not have been identified in previous literature that focussed on the short-term impacts of disasters.

The indirect effects appear to be dependent on the availability of credit (in the case of school enrollment rates), or on aid flows (in the case of health outcomes), in the aftermath of a disaster occurrence. This finding suggests that financing schemes should be viewed as an important policy response to disaster occurrences - and a crucial step in the long-term recovery process, alongside investment in infrastructure and physical reconstruction. The findings reported here are therefore of interest to both development specialists and policymakers alike. While aid flows may be sufficient to mitigate the health impacts of disasters, it appears that other measures - such as making finance or credit available to households, would be required to mitigate the longer-term impacts of disasters on educational attainment in affected regions.

Potential extensions of this research include a more direct investigation of household time allocation in the aftermath of disasters - possibly using survey data - and studies that explore the potential for financing schemes (micro-finance, weather-indexed insurance etc.) to ameliorate the human capital effects of disasters identified in this paper.

Table 1: Summary statistics for key variables

Variable	Mean	Std. Dev.	Min	Max
GDP (per capita)	8,873	10,358	280	78,798
Avg. Credit (% of GDP)	38.09	36.13	0	218.19
Net ODA (US$ per capita)	58.84	88.60	-3.06	1,024.38
Human Capital				
School enrollment (% of pop.)	58.35	32.75	2.40	154.75
Life expectancy (years)	64.13	10.49	28.87	81.57
Maternal mortality (per 100,000 births)	302.12	377.39	2	1,800
Infant mortality (per 1,000 live births)	50.49	39.40	2.6	176.76
Under-5 mortality (per 1,000)	74.36	67.18	3.46	314.88
Disasters				
Count measure	0.83	1.17	0	5
Sum measure (% of Pop Affected)	8.23	19.88	0	176.26
Binary measure	0.32	0.47	0	1

Table 2: Disasters and School Enrollment: Full Sample, Contemporaneous Effect

	Dependent variable: School enrollment rates											
	Binary Measure				Sum Measure				Count Measure			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Disasters	-2.7862***	-2.1234**	-2.6322**	-1.0744	-4.3003	-4.4819	-3.8846	-0.5930	-1.2595***	-1.0113**	-1.4061**	-0.4628
	(-3.23)	(-2.30)	(-2.13)	(-0.88)	(-1.37)	(-1.43)	(-0.82)	(-0.13)	(-2.75)	(-2.01)	(-2.16)	(-0.87)
lgdp		5.4592	5.4567	5.5044		5.4502	5.4481	5.7104*		5.4396	5.5615	5.7326*
		(1.61)	(1.60)	(1.63)		(1.62)	(1.62)	(1.67)		(1.62)	(1.63)	(1.68)
cred		0.1178**	0.1170**	0.1350**		0.1174**	0.1172**	0.1306**		0.1165**	0.1145**	0.1374**
		(2.17)	(2.15)	(2.30)		(2.10)	(2.10)	(2.15)		(2.16)	(2.12)	(2.33)
odapercap		-0.0228	-0.0248	-0.0231		-0.0226	-0.0224	-0.0223		-0.0211	-0.0246	-0.0213
		(-1.10)	(-1.16)	(-1.13)		(-1.08)	(-1.07)	(-1.07)		(-1.01)	(-1.14)	(-1.02)
Disasters*ODA			0.0091				-0.0086				0.0080	
			(0.58)				(-0.16)				(1.04)	
Disasters*Credit				-0.0395				-0.1507				-0.0173
				(-0.97)				(-1.08)				(-1.10)
Obs.	732	534	534	534	732	534	534	534	732	534	534	534
Countries	166	135	135	135	166	135	135	135	166	135	135	135
Adj. R-Squared	0.3786	0.5385	0.5381	0.5389	0.3719	0.5351	0.5342	0.5358	0.3772	0.5382	0.5387	0.5390

Note: Data in 5-year periods, from 1980-2004. All models include a constant term, and country and period fixed effects. Errors clustered at the country level. t-statistics in parenthesis. $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$.

Table 3: Disasters and School Enrollment: Poor Countries Only, Contemporaneous Effect

	Dependent variable: School enrollment rates											
	Binary Measure				Sum Measure				Count Measure			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Disasters	-1.9507**	-1.4830	-2.1345	-0.6790	-4.7302	-5.1625	-5.8843	1.4181	-0.6985	-0.9688*	-1.3304*	-0.0929
	(-2.05)	(-1.53)	(-1.48)	(-0.47)	(-1.41)	(-1.47)	(-1.11)	(0.27)	(-1.47)	(-1.74)	(-1.74)	(-0.18)
lgdp		6.4561	6.3843	6.6254*		6.3102	6.3089	6.9823*		6.5033	6.5654	7.1746*
		(1.63)	(1.60)	(1.68)		(1.61)	(1.60)	(1.74)		(1.65)	(1.64)	(1.79)
cred		0.2219***	0.2216***	0.2494***		0.2269***	0.2277***	0.2773***		0.2250***	0.2257***	0.2965***
		(3.43)	(3.44)	(3.07)		(3.54)	(3.57)	(4.02)		(3.59)	(3.62)	(4.20)
odapercap		-0.0016	-0.0069	-0.0013		-0.0016	-0.0019	-0.0019		0.0004	-0.0061	-0.0014
		(-0.05)	(-0.21)	(-0.04)		(-0.05)	(-0.06)	(-0.06)		(0.01)	(-0.19)	(-0.04)
Disasters*ODA			0.0107				0.0099				0.0068	
			(0.61)				(0.16)				(0.84)	
Disasters*Credit				-0.0383				-0.2885				-0.0314*
				(-0.55)				(-1.65)				(-1.94)
Obs.	381	336	336	336	381	336	336	336	381	336	336	336
Countries	88	85	85	85	88	85	85	85	88	85	85	85
Adj. R-Squared	0.3177	0.5288	0.5282	0.5284	0.3158	0.5305	0.5292	0.5355	0.3146	0.5317	0.5318	0.5372

Note: Data in 5-year periods, from 1980-2004. All models include a constant term, and country and period fixed effects. Errors clustered at the country level. t-statistics in parenthesis. $^{*}p < 0.10,^{**}p < 0.05,^{***}p < 0.01$.

Table 4: Dynamic effects of disasters on school enrollment: Full sample

	Dependent variable: School enrollment rates		
	Count measure	Sum measure	Binary measure
	(1)	(2)	(3)
Disaster	-3.9813***	-20.9473	-5.1806*
	(-2.77)	(-1.48)	(-1.76)
Dis*Credit	0.04878**	0.4519	0.0990
	(2.23)	(1.64)	(1.42)
Obs.	303	303	303
Countries	123	123	123
Adj. R-Squared	0.6060	0.5888	0.5964

Note: Data in 5-year periods, from 1980-2004 (except where lost due to lags). The reported coefficients represent the cumulative effect over 3 periods (contemporaneous effect and two lags), i.e. the cumulative effect at up to 15 years after the disaster event(s). The associated t-statistics are calculated in STATA using the *lincom* command. All models include a constant term, and country and period fixed effects. Credit was entered as a separate regressor in each model, along with income and ODA as additional controls. Errors clustered at the country level. t-statistics in parenthesis. $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$.

Table 5: Dynamic effects of disasters on school enrollment: Poor countries only

	Dependent variable: School enrollment rates		
	Count measure	Sum measure	Binary measure
	(1)	(2)	(3)
Disaster	-4.6996***	-39.1462***	-4.0565
	(-2.77)	(-2.82)	(-1.42)
Dis*Credit	0.0601**	0.8374***	0.1521**
	(2.65)	(2.90)	(2.07)
Obs.	191	191	191
Countries	77	77	77
Adj. R-Squared	0.6303	0.6122	0.6007

Note: Data in 5-year periods, from 1980-2004 (except where lost due to lags). The reported coefficients represent the cumulative effect over 3 periods (contemporaneous effect and two lags), i.e. the cumulative effect at up to 15 years after the disaster event(s). The associated t-statistics are calculated in STATA using the *lincom* command. All models include a constant term, and country and period fixed effects. Credit was entered as a separate regressor in each model, along with income and ODA as additional controls. Errors clustered at the country level. t-statistics in parenthesis. $^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$.

Table 6: Disasters and Life Expectancy: Full Sample

Dependent Var:	Life Exp				Life Exp Males				Life Exp Females			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Using the sum measure of disasters												
Disasters	-0.8399	-1.1487	-2.8751*	0.0121	-0.6853	-0.8719	-2.2903	0.2639	-1.0022	-1.4394	-3.4892**	-0.2524
	(-1.03)	(-1.19)	(-1.74)	(0.01)	(-0.82)	(-0.87)	(-1.26)	(0.15)	(-1.19)	(-1.47)	(-2.16)	(-0.13)
lgdp		2.2585***	2.2558***	2.3047***		2.0978***	2.0956**	2.1430***		2.4272***	2.4240***	2.4744***
		(2.70)	(2.69)	(2.75)		(2.62)	(2.61)	(2.66)		(2.73)	(2.72)	(2.77)
cred		0.0051	0.0057	0.0090		0.0010	0.0015	0.0049		0.0094	0.0101	0.0134
		(0.45)	(0.51)	(0.80)		(0.09)	(0.13)	(0.43)		(0.81)	(0.88)	(1.15)
odapercap		0.0057	0.0047	0.0057		0.0047	0.0039	0.0047		0.0068	0.0056	0.0068
		(1.29)	(1.09)	(1.29)		(1.10)	(0.92)	(1.10)		(1.44)	(1.23)	(1.45)
Disasters*ODA			0.0168*				0.0138				0.0200**	
			(1.73)				(1.38)				(1.98)	
Disasters*Cred				-0.0413				-0.0404				-0.0422
				(-0.89)				(-0.97)				(-0.81)
Obs.	853	610	610	610	853	610	610	610	853	610	610	610
Countries	171	141	141	141	171	141	141	141	171	141	141	141
Adj. R-Squared	0.3567	0.3474	0.3514	0.3478	0.3509	0.3530	0.3554	0.3534	0.3402	0.3243	0.3300	0.3246

Note: Data in 5-year periods, from 1980-2004. All models include a constant term, and country and period fixed effects. Errors clustered at the country level. t-statistics in parenthesis. $^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$.

Table 7: Disasters and Life Expectancy: Poor Countries Only

Dependent Var:	Life Exp				Life Exp Males				Life Exp Females			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Using the sum measure of disasters												
Disasters	-1.3385	-2.4115**	-5.7556***	-1.0533	-1.4237	-2.3175**	-5.5446***	-1.1654	-1.2490	-2.5101*	-5.9770***	-0.9357
	(-1.29)	(-2.05)	(-3.28)	(-0.52)	(-1.45)	(-2.14)	(-3.50)	(-0.63)	(-1.12)	(-1.96)	(-3.06)	(-0.42)
lgdp		2.7892***	2.7748***	2.8776***		2.4858***	2.4719***	2.5608***		3.1078***	3.0929***	3.2103***
		(2.81)	(2.83)	(2.86)		(2.68)	(2.71)	(2.73)		(2.89)	(2.92)	(2.96)
cred		0.0287	0.0319*	0.0391*		0.0223	0.0253	0.0311		0.0355*	0.0388**	0.0475**
		(1.56)	(1.84)	(1.96)		(1.28)	(1.56)	(1.65)		(1.81)	(2.09)	(2.23)
odapercap		0.0145	0.0141	0.0141		0.0115	0.0112	0.0112		0.0176	0.0172	0.0172
		(1.33)	(1.33)	(1.29)		(1.11)	(1.11)	(1.09)		(1.51)	(1.53)	(1.48)
Disasters*ODA			0.0377**				0.0364**				0.0391**	
			(2.48)				(2.61)				(2.36)	
Disasters*Cred				-0.0558				-0.0473				-0.0647
				(-1.08)				(-0.99)				(-1.16)
Obs.	440	378	378	378	440	378	378	378	440	378	378	378
Countries	88	86	86	86	88	86	86	86	88	86	86	86
Adj. R-Squared	0.2797	0.2817	0.2976	0.2818	0.3001	0.3042	0.3206	0.3040	0.2548	0.2595	0.2746	0.2600

Note: Data in 5-year periods, from 1980-2004. All models include a constant term, and country and period fixed effects. Errors clustered at the country level. t-statistics in parenthesis. $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$.

Table 8: Disasters and Other Health Outcomes: Full Sample

Dependent Var:	Maternal Mortality				Infant Mortality				Under-5 Mortality			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Using the sum measure of disasters												
Disasters	56.9938	56.5553	64.8993	40.2811	-0.6513	0.4461	6.7580*	-1.7091	2.4312	4.9386	17.4034**	1.5862
	(1.43)	(1.45)	(1.06)	(0.56)	(-0.26)	(0.16)	(1.69)	(-0.33)	(0.53)	(1.00)	(2.50)	(0.17)
lgdp		-168.2328***	-167.8060***	-168.9309***		-3.4200	-3.4211	-3.5081		-3.3203	-3.3224	-3.4574
		(-4.68)	(-4.63)	(-4.72)		(-1.21)	(-1.20)	(-1.22)		(-0.67)	(-0.67)	(-0.70)
cred		0.2650	0.2678	0.1898		0.0509	0.0487	0.0435		0.1170*	0.1126*	0.1055
		(0.68)	(0.68)	(0.50)		(1.39)	(1.34)	(1.11)		(1.82)	(1.77)	(1.55)
odapercap		-0.3375	-0.3281	-0.3404		-0.0279**	-0.0242*	-0.0279**		-0.0496**	-0.0424*	-0.0496**
		(-1.56)	(-1.48)	(-1.57)		(-2.08)	(-1.85)	(-2.08)		(-2.21)	(-1.93)	(-2.21)
Disasters*ODA			-0.1448				-0.0611***				-0.1206***	
			(-0.24)				(-2.63)				(-2.94)	
Disasters*Cred				0.6488				0.0772				0.1201
				(0.22)				(0.59)				(0.52)
Obs.	474	361	361	361	838	601	601	601	838	601	601	601
Countries	158	127	127	127	169	139	139	139	169	139	139	139
Adj. R-Squared	0.1572	0.3114	0.3095	0.3098	0.5880	0.6448	0.6487	0.6445	0.5282	0.5875	0.5932	0.5871

Note: Data in 5-year periods, from 1980-2004. All models include a constant term, and country and period fixed effects. Errors clustered at the country level. t-statistics in parenthesis. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 9: Disasters and Other Health Outcomes: Poor Countries Only

Dependent Var:	Maternal Mortality				Infant Mortality				Under-5 Mortality			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Using the sum measure of disasters												
Disasters	74.0625	63.5891	63.5240	108.5087	1.3065	3.2987	12.7031***	-4.6392	6.4778	9.6345	28.2060***	-2.4476
	(1.54)	(1.43)	(0.85)	(1.19)	(0.41)	(0.92)	(2.68)	(-0.73)	(1.10)	(1.48)	(3.54)	(-0.22)
lgdp		-182.8244***	-182.8287***	-179.1122***		-6.5798*	-6.5498*	-7.1021**		-7.8883	-7.8289	-8.6832
		(-4.71)	(-4.63)	(-4.59)		(-1.87)	(-1.87)	(-1.99)		(-1.35)	(-1.34)	(-1.46)
cred		-0.4248	-0.4248	-0.0954		-0.0060	-0.0152	-0.0667		0.0660	0.0477	-0.0265
		(-0.69)	(-0.69)	(-0.12)		(-0.10)	(-0.27)	(-0.88)		(0.63)	(0.47)	(-0.20)
odapercap		-0.5229	-0.5229	-0.5117		-0.0363	-0.0354	-0.0344		-0.0533	-0.0516	-0.0505
		(-1.12)	(-1.11)	(-1.09)		(-1.16)	(-1.13)	(-1.11)		(-0.99)	(-0.96)	(-0.94)
Disasters*ODA			0.0011				-0.1062**				-0.2098***	
			(0.00)				(-2.54)				(-3.05)	
Disasters*Cred				-2.0467				0.3259*				0.4961
				(-0.49)				(1.77)				(1.63)
Obs.	246	230	230	230	436	377	377	377	436	377	377	377
Countries	82	79	79	79	88	86	86	86	88	86	86	86
Adj. R-Squared	0.2531	0.3870	0.3842	0.3862	0.6515	0.6428	0.6507	0.6463	0.6221	0.6021	0.6127	0.6045

Note: Data in 5-year periods, from 1980-2004. All models include a constant term, and country and period fixed effects. Errors clustered at the country level. t-statistics in parenthesis. $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$.

Table 10: Dynamic effects of disasters on Life Expectancy: Full sample

Dependent variable:		Life Exp			Life Exp Males			Life Exp Females	
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Disaster measure:	Sum	Binary	Count	Sum	Binary	Count	Sum	Binary	Count
Disaster	-8.3757	-1.8191	-0.9077	-7.0211	-1.3859	-0.7514	-9.7980*	-2.2741*	-1.0718*
	(-1.58)	(-1.46)	(-1.66)	(-1.38)	(-1.18)	(-1.52)	(-1.75)	(-1.70)	(-1.75)
Dis*ODA	0.0548	0.0248**	0.0097**	0.0475	0.0200*	0.0076*	0.0625	0.0299**	0.0120**
	(1.26)	(2.00)	(2.09)	(1.18)	(1.78)	(1.80)	(1.32)	(2.17)	(2.29)
Obs.	370	370	370	370	370	370	370	370	370
Countries	139	139	139	139	139	139	139	139	139
Adj. R-Squared	0.2705	0.2731	0.2672	0.3066	0.3083	0.3024	0.2349	0.2388	0.2329

Note: Data in 5-year periods, from 1980-2004 (except where lost due to lags). The reported coefficients represent the cumulative effect over 3 periods (contemporaneous effect and two lags), i.e. the cumulative effect at up to 15 years after the disaster event(s). The associated t-statistics are calculated in STATA using the *lincom* command. All models include a constant term, and country and period fixed effects. ODA was entered as a separate regressor in each model, along with income and credit as additional controls. Errors clustered at the country level. t-statistics in parenthesis. $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$.

Table 11: Dynamic effects of disasters on Life Expectancy: Poor Countries Only

Dependent variable:		Life Exp			Life Exp Males			Life Exp Females	
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Disaster measure:	Sum	Binary	Count	Sum	Binary	Count	Sum	Binary	Count
Disaster	-14.2583**	-2.6817	-1.1909	-13.0684**	-2.1731	-1.0739	-15.5076**	-3.2156*	-1.3137
	(-2.25)	(-1.56)	(-1.58)	(-2.23)	(-1.34)	(-1.58)	(-2.25)	(-1.75)	(-1.58)
Dis*ODA	0.1068*	0.0357**	0.0145**	0.1006*	0.0303**	0.0121**	0.1134*	0.0414**	0.0170**
	(1.85)	(2.16)	(2.46)	(1.93)	(2.02)	(2.26)	(1.77)	(2.25)	(2.58)
Obs.	234	234	234	234	234	234	234	234	234
Countries	84	84	84	84	84	84	84	84	84
Adj. R-Squared	0.2689	0.2684	0.2560	0.2994	0.2947	0.2836	0.2407	0.2449	0.2310

Note: Data in 5-year periods, from 1980-2004 (except where lost due to lags). The reported coefficients represent the cumulative effect over 3 periods (contemporaneous effect and two lags), i.e. the cumulative effect at up to 15 years after the disaster event(s). The associated t-statistics are calculated in STATA using the *lincom* command. All models include a constant term, and country and period fixed effects. ODA was entered as a separate regressor in each model, along with income and credit as additional controls. Errors clustered at the country level. t-statistics in parenthesis. $^{*}p < 0.10,^{**}p < 0.05,^{***}p < 0.01$.

Table 12: Dynamic effects of disasters on Other Health Outcomes: Full sample

Dependent variable:	Maternal Mortality			Infant Mortality			Under-5 Mortality		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Disaster measure:	Sum	Binary	Count	Sum	Binary	Count	Sum	Binary	Count
Disaster	516.1516***	53.0693	30.8626	19.4365	-1.0457	-0.0035	45.8470**	-1.6554	0.3777
	(3.69)	(1.33)	(1.57)	(1.65)	(-0.35)	(-0.00)	(2.18)	(-0.26)	(0.15)
Dis*ODA	-3.3178***	-0.1339	-0.1593	-0.1991**	0.0265	-0.0083	-0.4140***	-0.0458	-0.0187
	(-2.78)	(-0.31)	(-0.80)	(-2.25)	(-0.97)	(-0.76)	(-2.72)	(-0.89)	(-0.92)
Obs.	337	337	337	366	366	366	366	366	366
Countries	126	126	126	137	137	137	137	137	137
Adj. R-Squared	0.4302	0.3826	0.3855	0.6337	0.6206	0.6156	0.5527	0.5346	0.5348

Note: Data in 5-year periods, from 1980-2004 (except where lost due to lags). The reported coefficients represent the cumulative effect over 3 periods (contemporaneous effect and two lags), i.e. the cumulative effect at up to 15 years after the disaster event(s). The associated t-statistics are calculated in STATA using the *lincom* command. All models include a constant term, and country and period fixed effects. ODA was entered as a separate regressor in each model, along with income and credit as additional controls. Errors clustered at the country level. t-statistics in parenthesis. $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$.

Table 13: Dynamic effects of disasters on Other Health Outcomes: Poor Countries Only

Dependent variable:	Maternal Mortality			Infant Mortality			Under-5 Mortality		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Disaster measure:	Sum	Binary	Count	Sum	Binary	Count	Sum	Binary	Count
Disaster	672.9451***	71.4774	53.8350**	33.6356**	-1.2251	1.8232	71.5468***	-1.0907	3.8738
	(4.51)	(1.20)	(2.09)	(2.60)	(-0.30)	(0.98)	(3.04)	(-0.13)	(1.10)
Dis*ODA	-4.4932**	0.0026	-0.1534	-0.2903**	-0.0179	-0.0128	-0.5945***	-0.0378	-0.0262
	(-2.61)	(0.00)	(-0.51)	(-0.47)	(-0.97)	(-0.88)	(-2.72)	(-0.50)	(-0.93)
Obs.	218	218	218	234	234	234	234	234	234
Countries	78	78	78	84	84	84	84	84	84
Adj. R-Squared	0.5093	0.4543	0.3855	0.6715	0.6492	0.6390	0.6064	0.5761	0.5733

Note: Data in 5-year periods, from 1980-2004 (except where lost due to lags). The reported coefficients represent the cumulative effect over 3 periods (contemporaneous effect and two lags), i.e. the cumulative effect at up to 15 years after the disaster event(s). The associated t-statistics are calculated in STATA using the *lincom* command. All models include a constant term, and country and period fixed effects. ODA was entered as a separate regressor in each model, along with income and credit as additional controls. Errors clustered at the country level. t-statistics in parenthesis. $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$.

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