The Impact of Natural Hazards on School Progression: Evidence from Rural Peru

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Abstract

The effect of natural hazards on human capital formation is a commonly overlooked aspect in assessing poverty-related impacts of climate change in developing countries. I estimate the effect of natural hazard damages to farmland on primary school grade non-completion rates in rural Peru. The results indicate that a damage of 42 hectares of average farmland, or 18 to 29 hectares of subsistence farmland, causes one schoolchild not to complete the grade she is enrolled in. Natural hazards thus account for several hundred yearly cases of grade failure in rural Peru.

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1 The Impact of Natural Hazards on School Progression: Evidence from Rural Peru

1.1 Introduction

One commonly overlooked aspect in the evaluation of natural hazard damages is its effect on educational production. In order to assess the costs of climate change researchers need to account for all of its effects on determinants of economic development; educational production resides prominently among them. Nevertheless, the most influential studies on the impacts of climate change and extreme weather events, the Stern Review on the Economics of Climate Change from 2006 and the Third Assessment Report of the Intergovernmental Panel on Climate Change (IPCC) from 2001[1], do not mention this facet at all. Natural hazards, however, can affect human capital accumulation via a number of channels. Particularly, disasters can distress the health and economic situation of schoolchildren and their families which may result in lower attendance, lower learning and higher dropout; in the long run this will negatively influence economic development.

This paper examines the impact of natural hazards on school progression in rural regions of Peru. The context of this paper is thus a developing country where particularly strong effects of extreme weather events to educational outcomes can be expected (IPCC

[1] Stern (2007), IPCC (2001)

2001). First, developing countries are geographically more exposed to extreme weather events than developed countries. Peru is estimated to be the third most affected country by climate hazards worldwide (Brooks, Adger 2003). Second, developing countries employ large shares of the population in the agricultural sector, which is most exposed to weather conditions. Third, developing countries have lower means of protection and insurance against extreme weather events. Incomplete financial markets and borrowing constraints impede consumption smoothing for many poor people. An extensive literature has found evidence for a worsening of educational outcomes in the face of negative income shocks (see second section).

The contribution of this paper is to extend this more general strand of literature on the effect of negative income shocks on educational outcomes in two respects. First, this paper considers natural hazards in rural regions of Peru as a specific type of negative shock. The effects of natural hazards in developing countries are interesting in their own respect. The third IPCC assessment stressed the vulnerability of poor countries which depend strongly on the primary sector to extreme weather shocks and their dire consequences for poverty reduction. However, we know little about the channels and magnitudes of these effects, which are important, for example to make cost-benefit calculations of climate change mitigation or to specify dynamic general equilibrium models.

Second, most estimates in the literature on the impact of negative income shocks on educational outcomes are vulnerable to the endogeneity of income. This is problematic in the presence of unobserved time-varying variables which may violate the key assumption of strict exogeneity of the regressors. This paper circumvents the endogeneity problem by exploiting natural experiments: I use disaster damage as an exogenous explanatory variable.

The analysis is based on a unique combination of longitudinal data bases at the district level in Peru. I combine information from a national disaster database, an agricultural census and the national school census. The main explanatory variable is the damage created by natural hazards in rural regions measured in hectares of damaged or destroyed farmland. The appeal of this variable is the exogenous nature of disasters which leads to a straight-forward identification strategy in fixed and random effects models. Also, hectares of farmland is an easily understandable magnitude which can be compared across countries. The key educational outcome examined is the share of enrolled primary schoolchildren being promoted to the next grade in rural areas. Furthermore, I examine the opposite, the share of students failing the grade either due to early withdrawal from school or due to non-promotion by the teacher. This strategy allows distinguishing different channels by which disaster damage causes grade non-completion. Additionally, the analysis is done for boys and girls separately to examine if effects differ depending on gender.

The results of the analysis suggest that damages to farmland caused by natural hazards such as floods, storms and fires have a pronounced impact on school progression in rural Peru. A disaster affecting one hectare of farmland per rural schoolchild decreases the rural district grade completion rate by an estimated 2.4 percentage points on average. Thus, for about 42 hectares of affected farmland one schoolchild is induced to fail the grade he or she is enrolled for. This average, however, understates the effect on small subsistence farmers with only up to 5 or 10 hectares of land. Further analysis suggests that a mean effect of up to one failing schoolchild per 18 hectares of affected farmland is possible if the whole district was owned by farmers with no more than 5 hectares of land each. Applying the mean prediction of estimates to the amount of disasters in Peru, the analysis accounts for about 1500 cases of grade failure in three years. Against common belief, withdrawal from school is not the only channel by which grade failure happens. A significant amount of children remains in school but is not promoted to the next grade – surprisingly, this effect is stronger when subsistence farmland dominates the area. Furthermore, the analysis suggests that there are no statistically significant differences between the effect on boys and girls when disasters occur. Due to large error bounds it is difficult to draw strong conclusions from these additional findings but they certainly represent an interesting area for future research.

Climate change is predicted to produce more frequent and severe weather events thus increasing negative impacts on educational outcomes and long-term human capital formation in developing countries. For example, the Andean Community estimates that Peru will have a 4.4 percent lower GDP with than without climate change by 2025, among other reasons by having 10 percent lower relative agricultural production (CAN 2008). It is imperial to focus further research on this issue to gain a clearer understanding of the channels and magnitudes of weather effects on education.

1.2 Background and Literature Review

Developing countries will be particularly distressed by the consequences of changing climatic circumstances and the increased frequency and severity of extreme weather events. (cf. Stern 2007, IPCC 2001). At the micro level, examples of direct consequences of climate hazards are loss of life, livelihood, private assets and infrastructure. At the macro level this translates into reduced productivity of important economic sectors, especially agriculture. The reasons for these effects are geographic exposure, low incomes, and greater dependence on the most climate sensitive agricultural sector. Latin America in general and Peru in particular are no exception in this respect. Charvériat (2000, p. 94) concludes that "the risk of natural disasters in the Latin American and Caribbean poses a sizable threat to the preservation and continuation of the regional socio-economic development process." Brooks and Adger (2003) from the Tyndall Centre for Climate Change Research conclude that Peru is the third most vulnerable country to climate-related natural disasters worldwide after Honduras and Bangladesh.

As a consequence, extreme weather events severely endanger the livelihood of farmers in developing countries who constitute a considerable share of the total population and are dependent on steady income flows from agriculture. In Latin America, almost 20 percent of the total area are agricultural lands, contributing about 10 percent to the region's GDP and providing occupation for up to 40 percent of the economically active population in some countries (IPPC, Chapter 14). The primary sector remains a key element of regional economies providing work and food security to many of the poorest people in rural regions. Especially subsistence farmers, who only produce for their own consumption, have little means to cope with unexpected shocks to small amounts of farmland as their primary sources of income and will be most affected by extreme weather conditions.

Peru in particular is a country with an accentuated subsistence farming sector which is vulnerable to negative weather shocks. According to the national agricultural census from 1994, 85.3 percent of agricultural production units are in the hand of small landholders with up to 10 hectares of land controlling about 49.4 percent of the total farmland. As a consequence, the largest share of agricultural workers is very exposed to extreme weather events. If a disaster damages farmland of such a small farmer the household is in danger of loosing the majority of income and would have to resort to coping strategies such as child labor. Nevertheless, disaster damage may also affect workers on industrial farms if their employers dismiss parts of the workforce in response to reduced arable surface.

A broader strand of literature has already considered the connection between negative income shocks and educational outcomes in developing countries and has generally found negative impacts. The connection between negative income shocks and decreased schooling runs through an increase in the supply of child labor, especially when there are credit constraints.[2] Such child labor is pervasive in Peru; Patrinos and Psacharopoulos (1997) find that rural children in Peru contribute on average 18 percent to family income. In general, Jacoby and Skoufias (1997) and Beegle, Dehejia, and Gatti (2006), among others, find that households significantly increase market work and decrease school attendance of children in response to anticipated and unanticipated income shocks. Yet, it is always difficult to address concerns of endogeneity of income even in a panel data setting. There may be unobserved time-varying variables correlated with income in different time periods, e.g. through investment decisions, which bias the estimated effect of income shocks.

This work also documents that there are important differences between boys and girls. Overall, girls tend to work more than boys (Edmonds 2007), especially in the household. Domestic work needs to be taken into account when considering the schooling-work trade-off, and can be a primary deterrent to school attendance (cf. Levison and Moe 1998 for Peru). As boys tend to have a smaller work burden in the household than girls, they face fewer barriers to schooling than girls (cf. Assaad et al. 2005 for Egyptian data).

Even though the vulnerability of school attendance to different forms of shock in developing countries is well-established it has so far not entered studies on the analysis of climate change related costs, such as the Stern Review or the IPCC report. Indeed, natural disasters can negatively affect educational outcomes via a number of channels on the demand and supply side of education. On the supply side, long periods of teaching may be lost due to adverse impacts of extreme weather events on the health and economic circumstances of instructors and the destruction or damaging of schools and relevant other infrastructure. On the demand side, schoolchildren and their families may also be affected in their health and economic situation which may result in lower attendance, lower learning and higher dropout. These channels, especially on the demand side, will be more accentuated in low-income countries. To my knowledge, Holmes (2002) is the only existing study which examines an effect of natural disasters on educational outcomes.[3] He analyses the effect of several hurricanes in North Carolina, USA, on student test score growth using a longitudinal school data set and finds a consistent negative effect.

This paper thus contributes to the thin literature on the connection between weather conditions and educational outcomes in developing countries. First, I use damages caused by extreme weather events as a specific shock which is interesting in its own respect to assess

[2] A great survey of child labor in general and its impact on school attendance is Edmonds (2007).

[3] Porta and Laguna (2007) indicate that hurricane Mitch may be responsible for a reversal of declining drop-out figures in Guatemala which, however, is not substantiated by an analysis.

the impact of climate change related events. Second, by the nature of this event, the econometric specification is straight-forward and I can circumvent many potential problems of endogeneity. Third, the impact expressed in hectares of affected farmland is an easily understandable magnitude which can be compared across countries.

1.3 Empirical Implementation

The focus of this paper is on the role of natural hazards in determining grade non-completion. The grade completion probability of a student is a function of two groups of factors: out-of-school factors, such as family and student characteristics, and in-school factors, such as school quality.

A household sending a child to school must have a positive expected value from enrollment. This value is determined by the difference between expected benefits of schooling for the child, such as future wages, and costs, such as fees and opportunity costs of not working in the household or labor market (see for example Gertler, Glewwe 1990).

However, if a poor household is hit by a shock, the expected value from going to school may change for enrolled children who may have to start supporting the family or increase their effort in doing so. This could mean dropping school for the current year or spending less effort on school tasks resulting in higher failure probability.

At an aggregate level, I specify the reduced form model

(1) $$y_{dt} = c_1 + \gamma_1 D_{dt} + \mu_d + \delta_t + e_{dt}$$

where grade completion rate y in district d at time t is influenced by a shock D which represents disaster damage relative to district size.[4] Also, there are district-level fixed effects μ and time effects δ.

If all students enrolled in school plan on finishing their current grade given current circumstances, e.g. family income, a negative shock to these circumstances may induce some of them to drop out or spend less effort on school, resulting in higher grade non-completion rates in the respective area. In a correctly specified econometric model, I expect to estimate a negative effect of a disaster shock.

[4] With grade completion expressed as a rate, district level variables need to be scaled in order to make them comparable across districts. My approach is to express disaster damage *per student* in the district, i.e., to chose the same denominator as for the dependent variable. The estimated result can thus be expressed as the number of hectares of affected farmland which induce one child less to complete the grade.

The analysis aims to establish whether the hypothesis of non-zero disaster effects can be rejected by estimating the above postulated relationship (1). The variable of interest is shocks to irrigated farmland, measured as hectares of farmland damaged or destroyed by some incidence, such as flooding, drought, fire or similar. In practice, other explanatory variables are not needed in the regression under the assumption that natural hazards are exogenous and thus uncorrelated with factors such as school quality and district poverty.

It is likely that the effect of disaster damage is not uniform across all units but may depend on local circumstances. In particular, a poor subsistence farming unit will be strongly affected by damaged farmland, whereas a large industrial production unit may be less so, especially for small amounts of damage. In (1), γ_1 will thus represent an average effect over all districts independent of their agricultural production structure. It is, however, also reasonable to estimate

$$(2) \qquad y_{dt} = c_2 + \gamma_2 D_{dt} + \gamma_3 A_d + \gamma_4 D_{dt}{*}A_d + \mu_d + \delta_t + \varepsilon_{dt}$$

where disaster damage is interacted with a factor A that characterizes the heterogeneity of districts with respect to their vulnerability to disaster shocks. In practice, I express this factor as the share of farmland in the district worked on by small-scale subsistence farmers.

It remains to be determined if (1) and (2) should be estimated by fixed effects or random effects regression. This leads to the question whether the observed shocks are truly uncorrelated with unobserved district fixed effects. If natural shocks are random only conditionally on an unobserved propensity for shocks, this problem can be solved via fixed effects regression.[5] Through demeaning of equations at several points in time, the problematic fixed effects including regional propensity for shocks are removed, such that there is no remaining correlation of the incidence of shocks and unobserved time-constant factors. If natural shocks are unconditionally random, both fixed and random effects estimation will be consistent but random effects will be efficient. The Hausman test can help to determine which specification to use.

A remaining source of concern is the possibility of unobserved time-varying factors which violate the assumption of strict exogeneity of the shock variables. This could be the

[5] Some areas are more likely to be hit by a shock than others, such as earthquake-prone areas, mountainous regions for droughts or wetlands for floods. If the resulting human conglomerations in this region evolve dependent on the area's specificities then the area's propensity for shocks is not exogenous in a cross-sectional regression. It may be correlated first of all with income and through this channel with other influential factors, such as vulnerability to shocks, school quality and individual ability, motivation and opportunity cost of schooling.

case if shocks have consequences which last for more than one period. For example, shocks may hit a community so hard that the poorest and possibly those students with lowest propensity to complete the grade drop out of school permanently. The unobserved overall ability of students may thus be higher in the next period, creating a correlation of ability and deviation from the mean shock.

1.4 Data

Different data sources are merged at the district level in order to enable estimation: data on 1) natural hazards, 2) on the distribution of farmland ownership and 3) on school completion and failure rates.

1.4.1 Natural Disaster Data

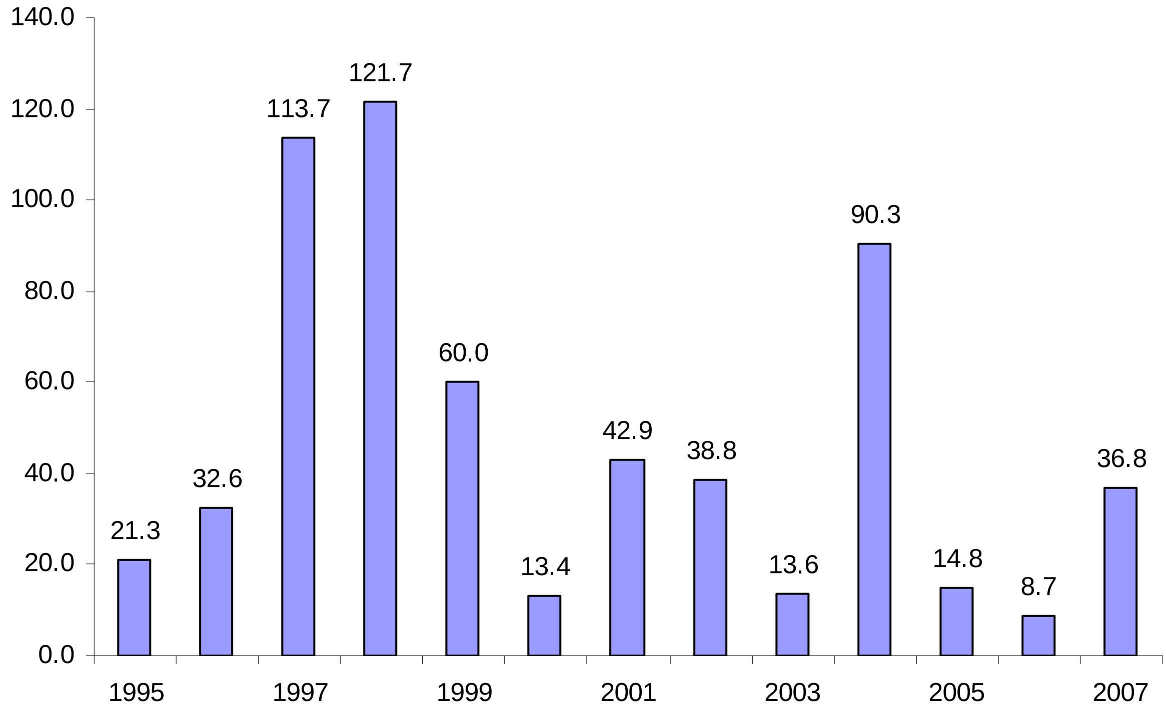
Information on natural hazards is retrieved from the Peruvian internet platform SINPAD (Sistema Nacional de Información para la Prevención y Atención de Desastres) which is part of the larger National Civil Defense System run by the National Civil Defense Institute. It is an internet-reporting system of damages and needs due to natural and human-caused disasters. The tool is used for official disaster monitoring, prevention and reaction. It is a uniquely comprehensive database which permits registering every single disaster in the country since 1995. For example, in the period January 1st 2003 to December 31st 2005 it contained more than 12,000 incidences of disaster in Peru.

Disasters contained in SINPAD are classified by phenomenon and linked to their respective damage, both in detailed categories. The types of phenomena contained are geodynamic, meteorological, biological or technological disasters. Also, the exact phenomenon is detailed, e.g., volcanic activity, earthquake, flooding, storm, landslide, drought, or fire. Furthermore, SINPAD registers the damages of disasters. These are classified into damages to life and health, buildings, ways of transport, agricultural infrastructure, farmland, crops and animals. In addition, the exact quantified damage is listed in the database, e.g., number of people deceased, hurt, affected, houses damaged and destroyed, or streets damaged and destroyed.

This paper uses information on damages to farmland as the main explanatory variable to measure shocks to rural areas and households. Within the disaster quantifications, SINPAD reports hectares of damaged and destroyed farmland which I aggregate to *affected farmland* as my main explanatory variable. These damages are clearly confined to rural areas.

Figure 1-1 shows the pattern of yearly reported hectares of destroyed farmland since 1995 and demonstrates that destruction of farmland by natural hazards is not a stable process. Instead, destroyed farmland varies between less than 10,000 and more than 100,000 annual hectares.

Figure 1-1. Destroyed Farmland in 1000 ha, 1995 – 2007



Source: SINPAD.

Table 1-1 shows the frequency and severity of disasters which affect farmland. Droughts are by far the most frequent and severe force in damaging and destroying farmland with 29 percent of incidences and 60 percent of affected farmland. Other high-frequency disaster phenomena with more than twenty incidences per year are frost, flooding, rain, hail and storm. Together, they account for more than 90 percent of affected farmland. Landslides, infestations and high tides are also on the list of severe disasters with more than 100 affected hectares per incident.

Table 1-1. Disasters Affecting Farmland, All Districts, January-December, 2003-2005

Phenomenon	Freq.	Percent Incidences	Affected Farmland (ha)	Percent Farmland Affected	Affected Farmland / Incident
Drought	303	29.2	339,234	60.45	1119.6
Frost	204	19.7	109,931	19.59	538.9
Flooding	172	16.6	58,643	10.45	340.9
Rain	103	9.9	19,088	3.40	185.3
Hail	74	7.1	7,778	1.39	105.1
Storm	60	5.8	7,203	1.28	120.1
Landslide	29	2.8	2,512	0.45	86.6
Fire	20	1.9	10,173	1.81	508.7
Flash Flood	20	1.9	680	0.12	34.0
Snow	14	1.4	681	0.12	48.6
High Tide	13	1.3	4,013	0.72	308.7
Alluvion	10	1.0	508	0.09	50.8
Collapse	6	0.6	301	0.05	50.2
Others (Ext. Geodynamic)	3	0.3	6	0.00	2.0
Others (Meteorologic)	2	0.2	57	0.01	28.5
Others (Int. Geodynamic)	2	0.2	14	0.00	7.0
Infestation	1	0.1	380	0.07	380.0
Earthquake	1	0.1	1	0.00	1.0
Total	1,037	100	561,203	100	541.2

Source: own calculations based on SINPAD.

The database dates back to 1995. While early years may suffer from underreporting there is no reason to believe that this is the cause for recent years. Disaster reports which end up in SINPAD are filed by local civil defense committees which exist in all districts in Peru. The filing of disaster reports is linked to the reception of aid measures which are also contained in the database. There is thus no reason to believe that reporting is endogenous, e.g., that poorer districts may not report all of their disasters.

Table 1-2 summarizes the frequency and severity of disasters affecting farmland that are relevant for the analysis. The sample of included districts and affected farmland figures is reduced in two ways compared to the whole population of disasters: excluding affected farmland in the months January to March and excluding districts which during those three years at some point of time reported a drought.

Hectares of farmland damaged or destroyed are added up from April to December of the respective year because this is the period of time which the school year spans. As a result, schoolchildren enrolled at the beginning of the school year in April will be affected by shocks to farmland from April on.

Drought-affected districts are excluded from analysis because droughts are longer term events and do not hit districts by surprise. For example, the department Tacna was reportedly in state of drought for more than two years during 2003 to 2005 while the incidence of drought was only reported once in the disaster database much later than the actual onset. The date of reporting thus cannot correspond to a day-specific realization of the disaster and cannot be congruently classified as before or after the start of the school year. This inaccuracy leads to the following problem: in case of reporting during the school year while the onset of the drought was before April, the drought will already have influenced the enrollment decision, an effect which I am not able to measure. Also, for droughts lasting longer than one year, the strict exogeneity assumption is less likely to be fulfilled. As a consequence, I find it most reasonable to exclude drought affected districts altogether even though they account by far for most of the damaged and destroyed farmland. However, it seems reasonable to believe that the estimated impact should be valid for all affected farmland independent of the disaster type which caused it, including droughts.

Table 1-2. Summary Statistics for Affected Farmland April-December, excluding drought-districts

Affected Farmland (Ha)	2003	2004	2005
All Districts			
Observations	1407	1407	1407
Mean	6.8	9.2	5.8
S.D.	73.5	98.3	138.1
Affected Districts			
Observations	49	64	32
Mean	193.8	202.2	252.8
S.D.	348.1	419.8	894.8
Max	1762	2374	5000
Total	9498	12939	8091
Affected Districts *(Ha/rural student)*			
Observations	49	64	32
Mean	0.14	0.19	0.23
S.D.	0.24	0.50	0.71
Max	1.05	3.43	3.82

Source: own calculations based on SINPAD.

The upper panel of Table 1-2 contains the disaster statistics measured in hectares of affected farmland for all districts including those which were not affected. The middle and lower panel show the disaster statistics only for affected districts – while the middle panel shows them in hectares of affected farmland the lower panel scales the statistics relative to the district primary school population, which is the relative measure later used in the regressions in order to make districts comparable in size.

During 2003-2005, out of 1662 districts 1407 were never affected by a drought. In 2003, 49 non-drought districts registered disaster-affected farmland, in 2004 64 districts, and in 2005 32 districts. Overall, 121 non-drought districts were at least once affected by a disaster-caused destruction or damaging of farmland.

Note that there are enormous differences between the sum of disaster affected farmland in Table 1-2 and Table 1-3. The difference stems from two sources: first, most disasters in Peru happen during the months of January to March; about 90 percent of farmland was affected during those months, as we can see in Table 1-3. Second, drought-affected districts are excluded from the regression sample. As a consequence, not only hectares of farmland damaged or destroyed by droughts are lost for the analysis but also all the remaining disasters in all three years of drought-affected districts.

Table 1-3. Total of Disaster-Affected Farmland, by Time of Year

Shocks to Farmland (Ha)	January - March	April - December
2003	40,975	9,772
2004	274,186	29,264
2005	183,678	23,328
Total	498,839	62,364

Source: own calculations based on SINPAD.

1.4.2 Distribution of Agricultural Production Units

In order to account for the structure of agricultural production in Peruvian districts, I use the Peruvian agricultural census (CENAGRO) from 1994 to approximate the share of land held by subsistence farmers in affected districts 2003 to 2005.

The CENAGRO was carried out between October and November of 1994 by the National Institute of Statistics and Informatics (INEI) and covered the entire country, excluding totally urbanized areas. The focal statistical unit is the agricultural unit, defined as any piece of land consisting of one or more parcels, totally or partially used for agricultural production, carried out as an economic unit by the agricultural holder, without regard to size, tenure or legal status. Data on holding and holder characteristics, tenure, land use and livestock etc. were collected through direct interview. The data used for this analysis only refers to agriculturally used land, not total surface.

Table 1-4. Total of Disaster-Affected Farmland, by Time of Year

Farmland production structure	National	Affected Districts	Affected Non-drought
Districts	1662	177	121
All sizes			
No. of units (in 1000s)	1671.22	234.15	170.72
Surface (in 1000 has)	5476.98	970.77	771.55
Average surface / unit (in has)	3.28	4.15	4.52
Units with <10 ha farmland			
Share of units	0.853	0.756	0.704
Share of surface held	0.494	0.407	0.362
Units with <5 ha farmland			
Share of units	0.710	0.579	0.511
Share of surface held	0.299	0.221	0.186

Source: own calculations based on CENAGRO.

Table 1-4 displays an overview of agricultural units in 1994, nationally compared to disaster-affected districts (in 2003 to 2005). Peru has almost 1.7 million agricultural units holding almost 5.5 million hectares of farmland. The average size is 3.3 hectares, compared to 4.2 hectares for all disaster-affected districts and 4.5 for disaster-affected non-drought districts. Nationally, about 85 percent of units work on less than 10 hectares, making up about 49 percent of the total farmland. In affected districts, 76 percent of units have less than 10 hectares and constitute 41 percent of total farmland. Typical subsistence farmers without production for market survive on 1 to 5 hectares of land (Plaza, Stromquist 2006) constituting 71 percent of units nationally and 30 percent of total surface. In affected districts, 58 percent of units work on less than 5 hectares, constituting 22 percent of total surface. Disaster-affected districts seem to be slightly bigger and less small-scale than the national average.

The numbers reveal that much of agricultural production in Peru is carried out on a very small scale, with the grand majority of farms working on less than 10 or 5 hectares of land. These farms and their workers can largely be considered subsistence farmers only producing for their own consumption. These production units are particularly exposed to extreme weather shocks due to lack of coping strategies.

1.4.3 Grade Completion Data

The third database used is the Peruvian school census 2004, 2005 and 2006 which covers all Peruvian educational institutions. It is collected on a yearly basis by the Ministry of Education via questionnaires specific to the type and level of institution. The survey information is self-reported by the schools. Schools are identified via a unique identification code and can thus be followed over time. Information is collected to reflect school registers at the date of May 30. The information collected does not allow for individual student profiles but aggregation at the grade and school level. For example, information contains the grade structure of students according to gender, age, native language and repeater status but it is not possible to follow who exactly is failing the grade.

Information on grade completion is collected for the previous school year such that the resulting database covers the end of year results for the years 2003, 2004 and 2005. The big advantage of the school census data is that it can be used to compare beginning of year enrollment with end of year results. Enrollment at the beginning of the year constitutes a revealed preference and signals positive utility from schooling. The panel setting with random effects allows using non-disaster affected districts as a control group to identify the average year specific rate of non-completion in the absence of disaster treatment.

In the school database, the enrollment and completion statistics are cleaned and added up to district figures only for schools in rural and marginal urban areas. Schools with inconsistent reporting or large enrollment changes over the years are excluded.[6] The subset used for estimation is a cleaned sample of formal, non-adult primary schools which are observed in all three years.

Table 1-5 summarizes the rural student population by year. In 2003, 81.5 percent of all rural primary schoolchildren completed the grade meaning that almost one in five children failed the grade. About 10 percent of children failed due to non-promotion while about 8

[6] Large changes in enrollment between years can stem either from structural breaks or strong measurement error, bot of which should be avoided. For example, in a school losing a large share of students due to a natural hazard in the area the remaining children may reflect a very different socioeconomic and ability structure and level. The school will thus not be comparable anymore and the strict exogeneity assumption needed for consistent estimation is violated. As a consequence, I may underestimate the effect of natural hazards if schools which are most severely hit are dropped from the sample.

percent failed due to early withdrawal or low attendance. There is a small but steady upward trend in promotion rates between 2003 and 2005.

The table indicates that there is no gender discrimination in rural Peru which can be found in the school system of many other developing countries. First, boys and girls constitute almost equal shares in the student population. Second, completion, non-promotion and withdrawal rates are equal among boys and girls in all years.

Table 1-5. Summary Statistics Rural Student Population

	2003		2004		2005	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Share Boys	0.511	(0.026)	0.511	(0.026)	0.510	(0.026)
All						
Share Promoted	0.815	(0.074)	0.827	(0.071)	0.833	(0.071)
Share Not Promoted	0.102	(0.043)	0.097	(0.045)	0.093	(0.044)
Share Withdrawn	0.082	(0.041)	0.076	(0.036)	0.073	(0.036)
Boys						
Share Promoted	0.815	(0.071)	0.825	(0.068)	0.831	(0.068)
Share Not Promoted	0.104	(0.043)	0.098	(0.044)	0.096	(0.043)
Share Withdrawn	0.081	(0.040)	0.076	(0.035)	0.073	(0.036)
Girls						
Share Promoted	0.816	(0.081)	0.829	(0.077)	0.835	(0.077)
Share Not Promoted	0.101	(0.047)	0.095	(0.048)	0.091	(0.047)
Share Withdrawn	0.082	(0.044)	0.076	(0.039)	0.073	(0.039)

Source: own calculations based on national school census, 2004-2006.

1.5 Results

Table 1-6 documents the main results of the paper from fixed (FE) and random effects (RE) estimation of specification (1), with and without year effects. The Breusch and Pagan Lagrangian multiplier test (not shown in table) strongly suggest the existence of individual effects such that FE and RE models are appropriate. The dependent variable is the district-level share of students successfully completing the school year and being promoted to the next grade. The independent variable of interest is the district-level amount of disaster-affected (damaged plus destroyed) farmland in hectares per rural student. The scaling is done to make bigger and smaller districts comparable. The estimation is performed on all districts which had not registered any drought throughout the period 2003 – 2005. The Hausman test strongly rejects significant differences between results from the fixed and random effects specification. This supports the view that natural disasters are unconditionally random events. In the following discussion I thus only report random effects.

Table 1-6. Disaster Impact on Grade Completion for Fixed and Random Effects Estimation

Dep. Variable: Share Completed	FE	RE	FE	RE
Farmland affected / rural schoolchild	-0.0220**	-0.0233**	-0.0225***	-0.0237***
	(0.0086)	(0.0093)	(0.0085)	(0.0087)
Constant	0.8085***	0.8084***	0.7970***	0.7969***
	(0.0001)	(0.0020)	(0.0010)	(0.0023)
Year Dummies	No	No	Yes	Yes
R^2	0.001	0.001	0.012	0.012
F (FE) / Chi2 (RE)	6.55	6.28	48.72	160.50
Observations	4221	4221	4221	4221
Hausman Test p-value	0.57		0.95	

Note: Robust standard errors in brackets. Significance levels: * p<0.10, ** p<0.05, *** p<0.01. Hausman test computed on regressions without robust standard errors which produce standard errors that never change the significance level of significant coefficients by more than 0.005 as compared to robust standard errors.

Both fixed and random effects results confirm a significant negative effect of disaster affected farmland on district grade promotion shares in rural primary schools. As the inclusion of year effects does not change the results (columns 3 and 4) we can be more confident about the exogenous nature of the explanatory variable. According to the results, a natural hazard damaging or destroying one hectare of farmland per rural schoolchild reduces the share of promoted students by 2.2 to 2.4 percentage points. In other words, for about 42 hectares of affected land, one schoolchild is not promoted to the next grade. Considering the total quantity of disaster-affected farmland between April and December 2003 to 2005, 62,364 hectares (Table 1-3), disasters forced about 1,500 students to fail the grade according to the mean prediction, not including those who were deterred from enrolling. If we assume that the same effect magnitude holds for children that were deterred from enrolling by disaster damage of about 500,000 hectares between January and March during those three years, almost 12,000 children were prevented to enroll in school.

Table 1-7 shows the results for random effects estimations according to specification (2), i.e., including affected farmland, a baseline effect for the share of small-scale agricultural units in the district, and an interaction term between the two. In the left panel, small-scale agricultural units are defined as those with less than 10 hectares of farmland, in the right panel, those with less than 5 hectares of farmland. In each panel, the first column contains only the non-interacted variables, the second column adds the interaction effect, and the third column assumes that there is no average disaster effect independent of the interaction effect.

Table 1-7. Disaster Impact on Grade Completion for Random Effects Estimation

	Subsistence farmland: < 10 has			Subsistence farmland: < 5 has		
Dep. Variable: Share Completed	[1]	[2]	[3]	[4]	[5]	[6]
Farmland affected / rural schoolchild	-0.0218**	-0.0165		-0.0223***	-0.0190*	
	(0.0086)	(0.0155)		(0.0086)	(0.0113)	
Share of subsistence farmland	-0.0471***	-0.0466***	-0.0460***	-0.0568***	-0.0557***	-0.0548***
	(0.0122)	(0.0122)	(0.0122)	(0.0180)	(0.0182)	(0.0182)
Farmland affected / rural schoolchild		-0.0176	-0.0546**		-0.0238	-0.0755**
x Share of subsistence farmland		(0.0426)	(0.0232)		(0.0506)	(0.0363)
Constant	0.7988***	0.7987***	0.7987***	0.7983***	0.7982***	0.7982***
	(0.0023)	(0.0023)	(0.0023)	(0.0023)	(0.0023)	(0.0023)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.019	0.020	0.019	0.017	0.017	0.017
Chi2	175.50	175.70	174.70	170.20	170.80	168.70
Observations	4221	4221	4221	4221	4221	4221

Note: Robust standard errors in brackets. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

For both definitions of small-scale farms, the results of column 1 and 4 do not change markedly compared to

Table 1-6 in the presence of subsistence farmland share as an additional regressor. Interestingly, the share of subsistence farmland is significantly associated with lower grade completion rates, possibly due to correlation with district-wide effects such as higher poverty or lower school quality. In columns 2 and 4, which include the interaction effect, affected farmland looses in magnitude and significance, dropping to -0.017 and -0.019. The interaction effect turns out negative for both subsistence definitions (-0.018 and -0.024) but insignificant, likely due to high correlation (0.99 and 0.97) with non-interacted farmland. However, in a Wald test (not shown), farmland and the interaction term are jointly significant at the 10 (colum 2) and 5 (column 4) percent level. Assuming that the mean effect is consistently estimated there would be both an average effect of disaster affected farmland and an effect that depends on the structure of farm holdings in the district. If every farm in the district is less than 10 hectares in size, the aggregate effect on grade completion is -0.033, for all farms having less than 5 hectares it is -0.043. In case of 100 percent subsistence farmland, the aggregate effect is thus such that 29 or 23 hectares of farmland devastation would cause one schoolchild to fail the grade.

Columns 3 and 6 of Table 1-7 confirm that there is a stronger negative effect of disasters if more farmland is held by smallholders, assuming that there is no average effect but only one that is dependent on local farmland structure. Column 3 shows a significant negative effect of -0.046 of the interaction term between affected farmland and the share of farms smaller than 5 hectares. According to RE, one child is induced to fail the grade for every 22 hectares of damage if farmland is completely held by agricultural units of less than 10 hectares. Column 6 reveals an even bigger significant effect of -0.089 such that one child is induced to fail the grade for every 18 hectares if farmland is completely used by agricultural units of less than 5 hectares.

Table 1-8 shows the results for random effects estimations similar to the one before only with the share of students not promoted and the share of students withdrawing from school before the end of the school year as separate dependent variables. These two categories constitute the aggregate of students failing the grade, i.e., 100 percent minus the completion share.[7] While we are ultimately interested in the share of those failing the grade due to the disaster for whatever reason an analysis of these categories separately may still be useful to learn more about the consequences of disasters.

Table 1-8. Disaster Impact on Grade Failure from Random Effects Estimation

			Subsistence farmland: < 10 hectares		Subsistence farmland: < 5 hectares	
Dep. Variable: Share	Not promoted	Withdrawn	Not promoted	Withdrawn	Not promoted	Withdrawn
Farmland affected / rural schoolchild	0.0078	0.0164*	-0.0154*	0.0314**	-0.0067	0.0255**
	(0.0071)	(0.0099)	(0.0093)	(0.0158)	(0.0047)	(0.0126)
Share of subsistence farmland			0.0425***	0.004	0.0523***	0.0033
			(0.0086)	(0.0067)	(0.0131)	(0.0099)
Farmland affected / rural schoolchild x Share of subsistence farmland			0.0703*	-0.0512*	0.0907**	-0.0649*
			(0.0383)	(0.0280)	(0.0439)	(0.0333)
Constant	0.1076***	0.0952***	0.1060***	0.0950***	0.1064***	0.0951***
	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0015)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.006	0.009	0.022	0.010	0.019	0.010
Chi2	62.06	97.57	91.03	98.77	84.10	99.17
Observations	4221	4221	4221	4221	4221	4221

Note: Robust standard errors in brackets. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

The point estimates for farmland affected by disaster per rural student indicate that about two thirds of those students who fail the grade because of a disaster shock do so because of withdrawal from school while about one third remains in school but is not

[7] A marginal difference between the sum of non-promotion and withdrawal share compared to 100 percent minus the promotion share can arise from students deceasing throughout the year who do not belong to either category.

promoted at the end of the year. Yet, the error bounds are too large to distinguish the effect sizes with certainty. When looking at the middle and right panels with a subsistence farmland effect plus its interaction, a different pattern emerges: it seems as if subsistence farming is much more associated with non-promotion than with withdrawal. The share of subsistence farmland is in both cases strongly associated with higher non-promotion but not higher withdrawal shares (second row). The average effect of damaged farmland is negative on the non-promotion share and positive on the withdrawal share (first row). In contrast, the interaction effect expresses that, compared to the average effect, a disaster in subsistence farmland areas drives up the non-promotion share and decreases the withdrawal share (third row). It is, however, unclear if the effects can be distinguished statistically. One possible reason for this pattern is that the rules for failing students due to insufficient attendance may be more relaxed in areas where many children frequently have to work in the fields. Another possibility is that workers in poorer subsistence farm areas may be more inclined to leave their children in school without intention to complete, e.g., for the benefit of free school meals.

Table 1-9 shows the results from random effects estimation on the sub-samples of boys and girls with the completion share of students as the dependent variable. In both cases, there is a negative effect of disaster affected farmland on the within-gender promotion share. This effect is only significant for boys, and the point estimate for boys (-0.030) is stronger than for girls (-0.020). Similarly, the disaster effect is stronger for boys than girls for the interaction with the share of subsistence farmland. However, the error bounds of these estimates are large such that equal effects for boys and girls cannot be rejected.

Table 1-9. Disaster Impact on Grade Completion for Boys and Girls from Random Effects Estimation

	Boys			Girls		
Dep. Variable: Share Completed	[1]	[2]	[3]	[4]	[5]	[6]
Farmland affected / rural schoolchild	-0.0299***	-0.0212***		-0.0200	-0.0214	
	(0.0075)	(0.0080)		(0.0146)	(0.0197)	
Share of subsistence farmland (<5 has)	-0.0476***	-0.0448**	-0.0437**	-0.0665***	-0.0669***	-0.0659***
	(0.0179)	(0.0178)	(0.0178)	(0.0187)	(0.0190)	(0.0190)
Farmland affected / rural schoolchild		-0.0618	-0.1195*		0.0102	-0.0480
x Share of subsistence farmland (<5 has)		(0.0768)	(0.0620)		(0.0536)	(0.0300)
Constant	0.7980***	0.7979***	0.7978***	0.7984***	0.7984***	0.7983***
	(0.0024)	(0.0024)	(0.0024)	(0.0026)	(0.0026)	(0.0026)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.014	0.015	0.014	0.016	0.016	0.016
Chi2	117.50	126.90	107.50	137.70	138.80	140.20
Observations	4218	4218	4218	4221	4221	4221

Note: Robust standard errors in brackets. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

Table 1-10 displays the results from random effects estimation on the share of non-promotion and withdrawal for boys and girls, for farmland affected and separately for affected farmland interacted with the two shares of smallholdings. For boys, all estimates suggest that the majority of grade failure due to disaster damage comes from non-promotion, not withdrawal. For girls, the picture is more ambiguous: the estimate for average affected farmland suggests that the effect for girls comes through withdrawal. When including the interaction effect, however, the pattern is the same as before: disaster shocks on subsistence farmland increase non-promotion, not withdrawal.

Table 1-10. Disaster Impact on Grade Failure for Boys and Girls from Random Effects Estimation

	Boys		Girls	
Dep. Var.: Share	Not Promoted	With-drawn	Not Promoted	With-drawn
A. Farmland affected / rural schoolchild	0.0216	0.0084	-0.0027	0.0226**
	(0.0132)	(0.0118)	(0.0088)	(0.0114)
B. Farmland affected / rural schoolchild	0.0091	0.0118	-0.0159*	0.0370***
	(0.0160)	(0.0158)	(0.0091)	(0.0133)
Farmland affected / rural schoolchild	0.0897	-0.0241	0.0939**	-0.1026**
x Share of subsistence farmland (<5ha)	(0.0640)	(0.0408)	(0.0394)	(0.0410)
Observations	4218	4218	4221	4221

Note: Results from random effects regression including the share of subsistence farmland and year dummies. Robust standard errors in brackets.

Overall, the results suggest that withdrawal from school, and possibly child labor, is not the only channel through which economic shocks hinder the school progression of rural children. Especially in areas characterized by subsistence farmland, disasters do not drive children out of school but lead to higher non-promotion shares. One possible explanation is that disasters induce a shift of time allocation from learning and homework to actual work in the labor market or tasks in the household which prevent sufficient learning achievement for grade promotion. As a result, the main counteracting policy could be both financial relief for households to deter child work but also improvements in the curriculum to transmit the learning materials more effectively in the available time.

1.6 Conclusion

This essay is one of the first to address the detrimental effects of climate change on human capital formation by estimating the effect of natural hazard damage in hectares of farmland on grade completion rates in rural Peru. I find that there is a significant detrimental impact of natural disasters on school progression. On average, 42 hectares of affected farmland are predicted to cause on student not to complete the grade. The estimate thus accounts for a mean prediction of about 1500 failing students in three years. The frequency and severity of climatic events is predicted to increase in the future thus creating more damage to human capital formation.

The focus of this paper is narrow as it only considers grade completion effects of farmland which is destroyed by catastrophic events. We can imagine many more channels of climatic events to affect the supply and demand of education, especially preventing children to constantly attend school and thus disrupting learning. Examples are the destruction of transportation and schooling infrastructure or health effects on teachers and students. Economic effects do not only stem from disaster damage. Maybe more importantly, temperature changes affect the productivity of farmland. Also, climate change is predicted to spur migration movements in developing countries which will certainly also reduce the amount of schooling attainable for children. Certainly, there is much more to learn about these effects to design appropriate coping strategies and prevent the loss of human capital which is so crucial for developing countries.

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