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Impact of Extreme Climate Events on Educational Attainment:

Evidence from Cross Section Data and Welfare Projection

UNDP/ODS Working Paper

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Abstract

This paper studies the impact of climate events on educational attainment. Instead of using multiple number of cross section or panel data sets, the educational attainment by age group in a single cross section data set is used to estimate the impact of historical climate shocks. The main empirical finding from Cameroon, Burkina Faso, and Mongolia data sets suggest that extreme climate events have long term negative impact on the educational attainment. In Cameroon, women who might have been affected by a drought are 8.7 percentage point less likely to complete primary school. In Burkina Faso, the drought reduced the probability for women to finish primary school by 1.9 percentage point, but the result is not statistically robust due to the low average in primary school completion. In Mongolia, the wild fire reduced the probability for individuals to complete secondary school by 14.4 percentage point. This paper also presents a benchmark figure of welfare loss caused by the climate events. In Mongolia, if there had been no wild fire in 1996, or if there had been a policy that protected households from the negative impact of the natural disaster, the average wage per worker, per year would have been 2.7% higher.

JEL classification: Q54; Q51; I2; I3

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1. Introduction

Although the climate change is not limited to extreme events, the response of households to climate changes is most measurable in such events. Extreme climate events include flood, drought, wild fire, and many other types of natural disasters. Should households be affected by these events, they adjust their economic behaviors to cope with the changes in their environment and resource.

The frequency of being affected by extreme events is not totally unexplainable. Some people often choose to live in an area that is known to be vulnerable to natural disasters. For instance, poor people can only afford houses that are located near the mountain and they get affected by landslides. Some people don't have resources to move out of a region that is frequently affected by a flood. Poor households are constrained by limited resource, and they are forced to get exposed to natural disasters, even if some of the risk is anticipated (World Bank, 2000). In this case, the frequency of being affected by the climate shock depends on their economic behavior.

Natural disasters not only affect the contemporary generation, but also following generations. They change the economic landscape of the affected areas, and often change the agricultural productivity in the long term. In many occasions, they destroy infrastructure, such as road, irrigation, drinking water pipes, schools and hospitals, and it takes many years to restore. There are irreversible impacts, such as death and disability. Extreme climate events are different from temporary shocks because their impacts are permanent or persistent for many years.

Climate related shocks can have prolonged impact on human development. Along with physical damage in landscape and infrastructure, they can affect the households' decision on the long term investment in human development. Increased exposure to droughts, floods and storms is destroying opportunities and reinforcing inequalities (UNDP, 2007, p.1). In order for governments and international communities to face this challenge with concrete policy options, scientific and empirical evidence of the human development impact of the climate change is urgently demanded.

Education is one of the most important measures in human development and has been carefully monitored by development communities. Table 1 describes the percentage of population that has attained at least upper secondary education, by age group in many developed countries. There is quite a large variation of average percentage of population that has attained at least upper secondary education among OECD countries, from 23% in Mexico to 89% in Czech Republic. Furthermore, the downward trend of the indicator across age group is commonly observed, because older generation typically had less chance to get higher education.

Many countries are working to be on track to achieve Millennium Development Goal 2, universal primary education.[1] Unfortunately, some part of the world is still left behind, especially

[1] United Nations, MDG (http://www.un.org/millenniumgoals/)

low income countries as seen in Figure 1. While high and middle income countries are approaching to 100% primary school completion rate, the average completion rate for low income countries still remain about 73% in 2005. There could be many factors contributing to this slow catch up by low income countries in educational attainment. Extreme climate events could be one of the factors that keep poor families from investing in their children's education. Measuring how much the extreme climate change can contribute to the loss of education opportunity would be the first step to design a coping policy for the developing countries.

I study the educational attainment profile in the regions that are prone to adverse climate shocks. The paper is organized as follows: Section 2 reviews previous studies on the risks and children's education, and Section 3 describes the methodology and data. Section 4 presents the empirical results with some welfare implication, and section 5 concludes the paper.

2. Literature review

A general empirical framework in the topic of climate change would be to find the relationship between two pillars: risk and human welfare. Specific research questions depend on how they narrow down and define the concepts of risk and human welfare. We can divide the studies in four groups, in order to reach the research question of this paper: shocks and human welfare; climate shocks and human welfare; shocks and education; climate shocks and education.

Shocks and human welfare. there is huge literature on general and broad discussion of the impact of shocks on human welfare. Dercon (2005) is a good start to see the description of climate risks, economic fluctuations, and a large number of individual-specific shocks leaving the households in developing countries vulnerable to severe hardship.

Climate shocks and human welfare. When we can focus on climate shock among the general risk, there are a variety of economic indicators that might be related to welfare in the literature. Household behavior can be analyzed as in Fafchamps et al (1998) that drought and savings in West Africa. Implication on poverty is among the popular research questions (e.g. Dercon and Hoddinott, 2003).

When we further narrow down the welfare measure to human development, a number of studies found the empirical evidence between natural disaster and human development indicators, health for example. Buttenheim (2006) studied flood exposure and child health in Bangladesh, Chrisiaensen and Alderman (2001) analyzed child malnutrition in Ethiopia, to name a few.

Shocks and education. Empirical relationship between education and risk in general has been studied from various perspectives. The factors that may affect the household decision to invest in children's education include shocks on household's income, demography, and policy change, etc. The education outcome has been measured in many different ways, such as school enrolment, grade advancement, performance at school, child labor.

There are studies on the impact of short term income shocks on children's education. Jacoby and Skoufias (1997) found that income fluctuations among the households in India lead to variability in school attendance. Duryea (1998) investigated the effects of short-run economic shocks on children's progress through school in urban Brazil using a panel data set. The empirical results showed that children's time is used to buffer short-run economic shocks to the household in the presence of imperfect credit markets. Jensen (2000) analyzed Cote d'Ivoire data to find children living in regions that experienced adverse weather shocks had lower investments in education and health.

Economy-wide shocks can also have micro impact on children's school enrolment. Ablett and Slengesol (2000) reviewed the experience in East Asian countries that suffered financial crisis in late 1990s, by focusing on the educational attainment measured by enrollment, dropout and continuation rates. The five countries under analysis showed a mixed impact of, and responses to, the crisis, depending on the varied levels of the education systems, the relative limited scope of the data, and so on. But the main conclusion is that the enrollment rates have not declined as much as feared, but the secondary enrollments seem to have been more affected than primary ones. It must be noted that children from poor households have been affected more severely than children from non-poor households, and the dropout indicator shows that poor families have withdrawn their children at a greater rate than their wealthier counterparts.

Climate shocks and education. Empirical evidence of the impact of climate shock on education started to receive attentions. Maccini and Yang (2008) studied the impact of historical rainfall for each individual's birth-year and birth-location with current adult outcomes from the 2000 Indonesia household survey data. It is mainly a paper on climate change and health impact, but they included the education outcome in their analysis. Higher early-life rainfall shows large positive effects on the outcomes of women. Women with 20% higher rainfall at the time of birth are 3.8 percentage points less likely to be poor, or in poor health, and complete .22 more grades of schooling.

The literature is very thin in the fourth group, that is, climate shocks and education, and there is not much evidence of the impact of natural shocks on education. This paper is in the line of research to investigate the specific empirical relationship between educational attainment and natural disaster. The research question is very specific, but the implication can be interpreted in the general framework of risk and human welfare as described above.

Additional studies on education. Education is hard to study without considering child labor decision. Studies on child labor have been accumulated. Orazem and Gunnarsson (2003) gave a nice summary of existing literature on this issue. The empirical relationship between child labor and children's human development is still mixed. There is indirect evidence that child labor limits a child's human capital development. Child labor has been linked to greater grade retardation (Sedlacek et al., 2003; Rosati and Rossi, 2001); lower years of attained schooling

(Psacharopoulos, 1997); and lower returns to schooling and a greater incidence of poverty as an adult (Ilahi et al, 2003). On the other hand, child labor and schooling may be complementary activities (Patrinos and Psacharopoulos, 1997).

Most of studies on child labor and school performance use the data in United States or developed countries. However, the impact of working and learning while in high school or college in developed countries may be very much different than that for young children working in developing countries. The number of studies on child labor and test scores in developing countries is limited, mainly by the lack of data. Sánchez et al. (2003) using Latin America data, and Heady (2003) using Ghana data are among the few studies.

Gertler and others (2004) showed that the demographic change can affect the investment in children's education. Loss of a parent is one of the most traumatic events a child can face. If loss of a parent reduces investments in children, it can also have long-lasting implications. The paper uses parametric and semi-nonparametric matching techniques to estimate how one human capital investment, school enrollment, is affected by a parent's recent death. The empirical analysis using Indonesia's survey during 1994-1996 finds a parent's recent death has a large effect on a child's enrollment.

While most of studies listed above examine adverse shocks, a positive policy shocks on children's education are also under analysis. Conditional Cash Transfer (CCT) is being implemented or under consideration in many countries. As Rawlings and Rubio (2003) summarized, planning and evaluation of CCT is done using household surveys by examining changes over time within treatment and control households. Collection of baseline and follow-up data allows difference-in-differences estimators to measure program impact.

3. Methodology and Data

3.1. Methodology

Difference-in-difference method is widely used to estimate the impact of a shock on human development indicator (for example, Dercon et al, 2007). The method in its classical form is particularly suited to assess the immediate impact of a shock on the treatment group (affected group) that is separated from control group (unaffected group). Figure 1 illustrates the method to estimate the impact of a shock on an indicator, for instance, the primary school enrolment rate between time t_0 and t_1. When a shock hits a group of people, the difference between the treatment group and the control group becomes wider. When the differences are evaluated statistically, the method can effectively measure the negative impact of the shock.

A typical difference-in-difference method requires some desired characteristics of the data. The shock under analysis should be one time (no repetition) and affects only identifiable group in an ideal case. At least two cross section data sets, or one data set with historical information is required to compare before and after the shock. If the composition of the sample groups are not consistent over time, a number of statistical treatment, such as propensity score matching, or one-to-one matching, are used to find the hypothetically identical twin, one of whom was affected, while the other wasn't (Skoufias and Shapiro, 2006).

The demand for micro level panel data becomes high in this field. Panel data will relax all these restrictions for empirical studies using the classical difference-in-difference method, by tracing individuals over time. Figure 2 illustrates hypothetical time series of an indicator for individuals, grouped in two. The economic behavior and outcome of the two separated groups are observable, and the impact of a shock can be measured at the individual level. As in Hoddinott and Quisumbing (2003) or Hoddintt and Kinsey (2001), the impact of shocks on consumption fluctuation or welfare for certain group can be estimated using panel data sets.

Unfortunately, nationally representative panel data sets with information about climate related shock are extremely scarce, even for developed countries. Given the consensus that adverse climate shocks are supposed to have more severe impact in developing world, the lack of micro level panel data can limit the extent of studies on developing countries (UNDP, 2007, p.76).

To go about the problem in panel data availability in developing world, this paper proposes to use the education profile in one cross section data set. Figure 4 plots the primary education completion rate by different age group from a hypothetical cross section data set. As see in Table 1, there is a downward trend across ages, because older generation had smaller chance to complete primary school. The figure is fictitious, but real data, for example, Guyana 2002 Census or United States 2007 Census show a remarkably similar trend.[2]

Hypothetically, one can observe the indicator is particularly low for the age group of 22, deviated from the trend in Figure 4. It suggests that a shock hits the age of 22 when they were school age children, about 10 years ago. The data do not record what happened to this group, for instance, what kind of shock affected them, how the enrolment changed, how many dropped out of school, how many came back to school, when they came back, etc. The enrollment could have fallen farther, government intervention might have happened, or the family might have moved to another region. After all these unobservable actions took place, what we observe in the data is how many of them actually remained in (or returned to) the school to get the certificate. Therefore, the indicator represents only the final net impact of a shock that hit the age group some years back. Since the shock might hit all children in the relevant age group, the age group of 21 and 20 might have been affected as well.

[2] Generally, census data with large number of observation shows a very smooth downward trend across age groups, while survey data with small sample size show some irregular deviations from the trend.

Notice that Figure 4 surprisingly looks similar to Figure 3. The trend across age group appears as a flipped image of the time series information using the panel data. Should the group of people who were affected by historical shock be carefully identified, the estimation for the impact of the shock can be done with cross section information in Figure 4. The method used for Figure 4 would need only one cross section data set, while the approach in Figure 3 should use a panel data set that is hardly available in developing countries. The approach in Figure 4 can extend the use of cross section survey to do useful analyses of climate related risks or vulnerable group, as demanded by Hoogeveen et al (2008).

This method can be regarded as an expanded type of difference-in-difference method that uses only single cross section data as in Duflo (2001) and it has some merits and demerits. Studying the final outcome of individuals using historical disaster shock focuses, by design, only on the long term net outcome. It cannot explain movements of short term indicators of individual, household, or government behavior to cope with the shocks. However, if the research interest is to study the long term impact of the climate events, which is precisely this paper is about, long term final outcome must be the indicator to be analyzed.

3.2. Specification

The empirical estimation is specified as follows:

$$\text{(Eq 1)}\; S_i = \beta_0 + \vec{\beta}_1 \mathbf{D}_i + \beta_2 G_i + \beta_3 G_i^2 + \vec{\beta}_4 \mathbf{X}_i + \varepsilon_i \qquad \text{for i} = 1, \cdots \text{N}$$

where

$$S_i = \begin{cases} 1 & \text{if i completed primary education} \\ 0 & \text{else} \end{cases}$$

$$\mathbf{D}_i = \left(D_{i1}, \cdots, D_{ij}, \cdots, D_{iJ}\right)'$$

$$D_{ij} = \begin{cases} 1 & \text{if i was affected by jth disaster, } D_j \\ 0 & \text{else} \end{cases}$$

$$G_i = \text{Age of i}$$

$$\mathbf{X}_i = \text{Individual charateristics of i}$$

$$\varepsilon_i = \text{idiosyncratic random error}, \quad E(\varepsilon_i) = 0$$

The limited dependence variable, the dummy for primary school completion, is regressed on series of disaster dummy variable and age, at the individual level. Notice that the model can incorporate multiple disaster dummy variables (D), as long as the individual is identified by the previous disasters. Age (G) is included because the downward trend of school completion across age is commonly observed in many countries. The square term of Age (G^2) is included in the estimation because the downward trend is often curved with increasing marginal effect as the age increases. Other control variables (X) can include individual characteristics, such as region, ethnicity, religion, gender, marital status, etc.

The most important omitted variable in this specification would be the income of the person's parent. Schooling is likely to be correlated with the income level and poverty status. To be more specific, the education level of a person is likely to be determined by the income level of her parents, not her current income, because her education is likely to determine her current income level (Heckman et al, 2003). For this reason, if an income variable is to be included in the regression, the household income when she was a child should be considered, instead of her current household income. Unfortunately, the household information when the person was young is very limited in the data. A good instrumental variable that is highly correlated with the parent's income but not with the person's current income would improve the empirical results without doubt.[3]

The person's position in poverty status might affect the precision of the model as well. It is usually assumed the error term (ε_i) has the property of homoskedasticity, that is, the variance of the error term does not depend on individual i. However, should the poor people have an unexplainable factor in their schooling determination and the factor varies more than that of non-poor people, then we may have heteroskedasticity which will make the estimator still unbiased but not most efficient. In reality, if poor people have smaller number of means to insure against unexpected shocks on their schooling, this might be the case. Because the usual t-test using standard error of estimator would fail in case of heteroskedasticity, I use the heteroskedasticity-consistent standard error (or robust standard error) to test the significance of the estimator.

Using historical disaster information can reduce the explanatory power of the model. Theoretically in the model, we can include all individual in any age group, and all disasters in the past. But in this case, as we approach to older people, there will be sample selection bias in surviving adults, and also heteroskedasticity (increasing variance of error term for old people). To minimize the extent of this problems, I restricted the sample to less than or equal to 35 years old. Estimating the impact of a disaster that happened 10 years ago would be much more efficient than estimating the impact of a 30 years old disaster, for example.

The model does not limit the number of disasters in the regression. However, if we included many disaster dummy variables, we might encounter a multicolinearlity problem when the disasters are correlated among one another. In fact, evidence is being accumulated that climate change and global warming increased the frequency of extreme climate events, and the disasters occur in some areas repeatedly (UNDP, 2007, p.75). Therefore, having too many disaster variables in the model will ultimately eliminate the explanatory power of the regression because

[3] A good candidate for such an instrument would be the education level of the parents. But the information is not available in most of the data.

the impact of shocks will be permanent for all age groups in the extreme case. In practice, we would have to test multicollinearity and the quality of the disaster data.

The data quality of developing country is often questionable with a possibility of large measurement errors. Using data for developed countries might be a way to evaluate the model specification. However, using developed country data has a different set of problems. First, it is difficult to choose a meaningful education indicators if almost everyone receives primary and secondary education. Second, the mitigation policy against risk is well developed in high income countries. It is often observed that the negative impact is neutralized by government interventions, and sometimes people who are affected by bad shocks become better off than before because of the generous subsidy.

3.3. Data

To identify individuals who were affected by extreme climate shocks, I use Emergency Events Database (EM-DAT). It is collected by World Health Organization (WHO) collaborating Centre for Research on the Epidemiology of Disasters (CRED), and the data covers the occurrence and effects of over 16,000 mass disasters in the world from 1900 to present.[4]

The disasters listed in the EM-DAT fulfill at least one of the four criteria: Ten or more people reported killed; 100 or more people reported affected; Declaration of a state of emergency; Call for international assistance. The database covers various events including natural and non-natural disasters. Since it is designed for disaster preparedness and risk management, identifying sub-group of population who were directly or indirectly affected at the micro level is not an easy task. The database records the geographical information of disasters. Combined with the timing of the event, the people who lived in the affected area at the timing of the event are assumed to be affected by the climate shock.

For the education outcome, different data sets can be used as long as they include the necessary information. Typically, one of following data sets is available for developing countries: Demographic and Health Survey (DHS), Living Standard Measurement Survey (LSMS), Labor Force Survey (LFS), and Population Census. In this paper, DHS data sets are used for Cameroon and Burkina Faso, and LSMS for Mongolia. The selection of countries was made randomly, in order to pick exemplary cases in each continent. Since the data for these three countries don't have much historical information on the income or disasters, the analysis in this paper will allow us to test if we can have a meaningful analysis with minimum amount of data.

The history of collecting detailed household level data for Cameroon and Burkina Faso is short. If we can use DHS data for these countries in Africa, then we will be able to expand the study to other countries easily. DHS are nationally-representative household surveys that provide data for a wide range of monitoring and impact evaluation indicators in the areas of population, health,

[4] For descriptive statistics of the dataset, see EM-DAT website (http://www.emdat.be/)

and nutrition. The survey topics covered in DHS are child health, education, family planning, fertility, domestic violence, HIV, infant mortality, nutrition and so on.[5] Since DHS are designed to study the wellbeing of children and mothers, information on adult population is collected only for women with age of 15 or more. With this reason, the analysis on Cameroon and Burkina Faso is done only for women.

When we have the information on income data, we can do richer analysis. I use Mongolia LSMS data to study the impact of disasters on education, and also income. The main objective of LSMS surveys is to collect household data that can be used to assess household welfare, to understand household behavior, and to evaluate the effect of various government policies on the living conditions of the population. Accordingly, LSMS surveys collect data on many dimensions of household well-being, including consumption, income, savings, employment, health, education, fertility, nutrition, housing and migration.[6]

Table 2 describes the basic statistics of the datasets. About 65% of women in Cameroon completed primary school. Females are much less likely than males to complete any education, but in general, indicators of the gender inequality in education are better in Cameroon than most of many sub-African countries (UNDP, 2007, p.336). Since the standard deviation (.47) across individuals is big enough, the primary completion has statistically meaningful variations to be analyzed by regression analysis.[7]

In Burkina Faso, the primary school completion rate for women is very low (11%). Living in one of the poorest countries in the world, women in Burkina Faso is a very vulnerable sub-group.[8] Low educational attainment for women can explain in part that young women tend to be more involved in the service subsector of the informal economy which is likely to be less profitable and more vulnerable (Calves and Schoumaker, 2004, p.1351). Because there are not many women who completed primary or secondary education, it is not easy to get statistically significant estimates for the coefficients when the school completion is regressed on explanatory variables.

I use secondary school completion (54%) for the statistical analysis in Mongolia, because most of sample (96%) completed primary school. Since 1989, there have been ongoing reforms in Mongolian education system from a highly specialized and compartmentalized system based on the Russian model to a more flexible system. Primary education is provided almost universally, and the focus of the reform strategy shifted to higher education level (Weidman, 2002, p.101). Therefore, using secondary education completion is more appropriate in the Mongolian context.

[5] Measure DHS, (http://www.measuredhs.com/)
[6] World Bank, LSMS (http://www.worldbank.org/LSMS/guide/describe.html)
[7] Completing primary education does not help much increasing their wage. The wage premium is almost zero between no school and primary school, while secondary education yields higher earnings (Ewoudou and Vencatachellum, 2006, p.7).
[8] It ranked 176th of 177 countries in the UNDP's human development index (UNDP, 2007)

Using secondary education instead of primary education may have different implication, because behavioral responses might be complicated. For example, households and children might be more invested in the secondary education, so they are less likely to drop out in the event of a disaster. On the other hand, the school fee is more expensive for the secondary school, and the opportunity cost of remaining in the school (wage in outside market) would be higher, so they are more likely to drop out than at a primary school. Therefore, the impact on secondary school is difficult to be determined as overestimated or underestimated. It should be interpreted cautiously if we compare the result across countries and across estimation models.

The LSMS 2002 data in Mongolia includes a module on dropouts. The module was included in the survey to evaluate the dropout situation in the country, and to design/evaluate a conditional cash transfer program to increase school enrolment.[9] The questions included in the module can describe why the students dropped out of school, and provide some subjective information.

Table 3 shows that there are 435 drop-outs from primary school and they are between 8 and 35 years old. Reasons for leaving school vary, but about three of them seem to be related to the income change of the household: lack of budget (12%), required to work (12%), or required to look after others (4%).[10] Among the drop-outs, 39% of them want to go back to school. They responded that they can’t go back to school because of lack of budget (50%), not qualified (19%), or busy (10%).

4. Result

4.1. Regression result

Table 4 reports the estimation results for Cameroon, Burkina Faso and Mongolia. The Probit estimation is done using primary or secondary school completion as the limited dependent variable. Rather than reporting the coefficients, the table reports the marginal effect, that is, the change in the probability for an infinitesimal change in each independent, continuous variable and reports the discrete change in the probability for dummy variables.

In the analysis, only one disaster dummy variable is used for each country’s regression, although the specification in this model does not limit the number of disasters in the regression. Since I

[9] Child Money Program which is a conditional cash transfer supported mainly by the Asian Development Bank was implemented in Mongolia by Ministry of Social Welfare and Labor. See UNICEF (2007) for an overview and poverty implication of the program.

[10] Note that there could have been multiple reasons for a person, but only one answer could be chosen in the questionnaire. For instance, if a person dropped out because he was not interested, his parents not interested, and lack of budget, he could answer any of these three.

chose the countries where high quality and large sample data is not available, including multiple number of disaster variables significantly reduces the explanatory power of the regression model.

The first column of Table 4 displays the coefficient estimates for Cameroon. In 1990, a drought affected 186,900 in north province. Individuals who were school age children in 1990 and lived in the north province are identified as affected group. The weighted Probit regression is done for all women with age between 15 and 35. Religion, ethnicity, and region are controlled out.

In Cameroon, the people who were affected by the drought in 1990 are 8.8 percentage point less likely to finish the primary school. The coefficients for age variables are also significant, suggesting there is a nonlinear relationship between the age and primary completion. The regression fits relatively well in terms of R^2 (52%).

The second column represents the results for Burkina Faso. In 1988, a drought affected 200,000 in north province. The weighted Probit regression is done for all women with age between 15 and 35. Religion, ethnicity, and region are controlled out.

In Burkina Faso, the result is less robust. People who might have been affected by the drought in 1988 are 1.9 percentage point less likely to complete primary school, but the coefficient estimate is not statistically significant. Coefficient estimates for age variables are not significant, either, and the regression model does not perform well (R^2=18.6%). Since many of women do not complete primary or secondary school as described in Table 2, the estimation using school completion is limited as expected.[11]

The last column shows the estimation result for Mongolia. In 1996, a wild fire affected 5,000 people in several areas, such as Huvsgul, Bulgan, Arkhangai, Khentii, Tuv, Dornod, and Uvs. It affected rather small number of people, but the impact was concentrated in rural areas, such as Highlands and East regions (2.3% and 4% of people in each region have non-zero disaster dummy variable). Winter storm is the most frequent disaster in Mongolia. However, the regression using winter storms as the disaster variable does not perform well, probably because the storm hits the country when the school is in break, or because the storm doesn't have long term impact on households as wild fire does. Gender, marital status, and region are controlled out in the regression.

In Mongolia, the wild fire in 1996 reduced the probability to finish secondary education by 14.4%. And the result is significant at 99% confidence level. The coefficient estimate for SEX is

[11] Logit estimation using Burkina Faso data does not provide statistically significant results, although Logit regression generally performs better for this type of case.

negative, suggesting that the probability for men to complete secondary school is 17.2 percentage point lower than that for women.[12]

In summary, the coefficient estimates for disaster variables are all negative and some of them are statistically significant. People who might have been affected by a disaster when they were school age children ended up with lower accomplishment in education. It should not be interpreted as that all the impact is directly related to disaster, because it is an analysis based on historical shock and long term outcome with unobservable household behaviors. However, the result shows that the impact is not negligible, and it is possible to measure the impact without multiple cross section or panel data sets.

4.2. Welfare impact

Once the impact of disasters on education is estimated, the potential welfare loss from this lost educational opportunity can be projected as follows:

Step 1:

From (Eq 1) $S_i = \beta_0 + \beta_1 \mathbf{D}_i + \beta_2 G_i + \beta_3 G_i^2 + \beta_4 \mathbf{X}_i + \varepsilon_i$,

get $\hat{\beta}_0, \hat{\beta}_1, \hat{\beta}_2, \hat{\beta}_3, \hat{\beta}_4$

$\hat{S}_i = \hat{\beta}_0 + \hat{\beta}_2 G_i + \hat{\beta}_3 G_i^2 + \hat{\beta}_4 \mathbf{X}_i$ (counterfactual probability of schooling, no shock)

$S_i^c = \begin{cases} 1 & \text{if } \hat{S}_i > \overline{\mathrm{C}} \\ 0 & \text{else} \end{cases}$ (counterfactual schooling dummy)

Step 2:

(Eq 2) $W_i = \alpha_0 + \alpha_1 S_i + \alpha_2 \mathbf{Z}_i + \mu_i$ where $W_i = \log(\text{wage of i})$, $Z_i =$ control variables, $\forall \text{i}$, $E(\mu_i) = 0$

get $\hat{\alpha}_0, \hat{\alpha}_1, \hat{\alpha}_2$,

$W_i^c = \hat{\alpha}_0 + \hat{\alpha}_1 S_i^c + \hat{\alpha}_2 \mathbf{Z}_i$ (counterfactual wage)

Step3:

$$(\text{Eq } 3)\ L = \frac{1}{N} \sum_i (W_i^c - W_i)$$

First step is to get the counterfactual schooling dummy variable, assuming there was no disaster at all. The coefficient estimates from Eq 1 are used to project the probability of completing a

[12] SEX=1 for men, SEX=0 for women. The overall average rate of secondary school completion is higher for women (58.7%) than men (48.3%). Author's calculation from Mongolia 2002 LSMS.

school ($\hat{S}_i$), taking all disaster variables as zero. The projected value is the counterfactual probability to complete primary or secondary school, should there be no disaster. Then the probability is converted into a counterfactual schooling dummy variable (S_i^c) that represents the primary (or secondary) school completion. The cutoff value ($\bar{C}$) can be arbitrary, and the result will show slightly different outcomes depending on this threshold.

Step Two is to estimate how much the schooling contributes to the wage. Using a simple Mincer regression, the estimate for return to education ($\hat{\alpha}_1$) can represent how much more the person will earn if the person has completed primary or secondary education. Typical Mincer regression includes experience and its square term in Z_i. Since the experience is not collected in the data, I used the person's age and its square term as the regressors. Using the estimated coefficients and counterfactual schooling, I calculate counterfactual wage (W_i^c).

The final step is to calculate the potential average loss of income by subtracting the actual wage from the counterfactual wage. If there is no disaster, the probability to complete school would have been higher, and the wage would have been higher. The difference between these actual and counterfactual wage can be used as a benchmark that shows the potential loss of income caused by disasters.

Note that this final step assumes an egalitarian social welfare function: all individuals are weighted evenly. This is a strong assumption to make in welfare analysis, and Rawlsian weights giving more weights on poorer households are often used as an alternative. The welfare analysis in this paper is meant to be illustrative and preliminary, using egalitarian weight is good enough to serve our purpose. However, using Rawlsian weights is expected to result in a bigger welfare impact because poorer households are more likely to be affected by the disasters.

To give a little more intuition for this loss function,

By adding and subtrating,

$$L = \frac{1}{N}\sum_{\text{i}} \{(\hat{\alpha}_0 - \alpha_0) + (\hat{\alpha}_1 S_i^c - \hat{\alpha}_1 S_i) + (\hat{\alpha}_1 S_i - \alpha_1 S_i) + (\hat{\alpha}_2 \mathbf{Z}_i - \alpha_2 \mathbf{Z}_i) - \mu_i\}$$

By some arithmatics and using $E(\hat{\alpha}_{\bullet} - \alpha_{\bullet}) = 0,\ \ E\mu_i = 0,$ and $E(S_i^c - S_i) = f(D, \beta_1, \cdots)$

$$E(L) = \frac{1}{N}\sum_{\text{i}} \left\{E(\hat{\alpha}_1(S_i^c - S_i)) + E((\hat{\alpha}_1 - \alpha_1)S_i)\right\}$$

$$= \frac{1}{N}\sum_{i} \left\{E(\hat{\alpha}_1) \bullet E(S_i^c - S_i) + Cov(\hat{\alpha}_1, S_i^c - S_i) + E(\hat{\alpha}_1 - \alpha_1) \bullet E(S_i) + Cov(\hat{\alpha}_1 - \alpha_1, S_i)\right\}$$

$$= \frac{1}{N}\sum_{i} \left\{\alpha_1 E(S_i^c - S_i) + Cov(\hat{\alpha}_1, S_i^c - S_i) + Cov(\hat{\alpha}_1 - \alpha_1, S_i)\right\}$$

$$= \frac{1}{N}\sum_{i} \left\{\alpha_1 f(D, \beta_1, \cdots) + \cdots\right\}$$

When we focus on the fist term of the equation, the link from disaster to economic loss of welfare is clear. When the probability of being hit by a disaster changes (D), it is lead to a loss of educational opportunity by the amount of (β_1), which will determine the expected value of the difference between the counterfactual schooling and actual schooling. Then the loss of education affects the individuals by the return to education coefficient (α_1).

Table 5 summarizes the result of this simple exercise using the secondary schooling and wage distribution in Mongolia using the cutoff point being .4. The loss of income is estimated as $17 per person, per year. This is about 2.7% of current average wage, and the result is almost the same using only male sample. Therefore, holding everything constant, the average individual wage would be 2.7% higher than now if there had been no disaster or if the disaster had been completed hedged.

The result varies with the cutoff point ($\bar{C}$) used in Step One. The main result presented in Table 5 uses .4 that produces the average primary completion rate in the original projection with disaster dummies. When we apply different values for the cutoff point varying from .3 to .5, the projected change of income ranges varies from 2.1% to 3.5%.[13]

Note that this analysis is illustrative, and consider only the average impact. The impact of a disaster would probably more on the distribution side, not the average of income. Poor people tend to earn low wage with low education, and they are more likely to be vulnerable to disasters. If there is no disaster, they are the one who will mostly benefit from increased educational opportunity.

Note also that this analysis is by a static projection, assuming there is no change in the return to education. If there is larger number of secondary school graduate in the no-disaster scenario, the wage level would change for different educational groups of people by demand-supply interaction. In the event of extreme climate shock, when more people drop out of school, unskilled wages could decrease and skilled wages increase depending on how wide-spread the disaster was and how mobile workers are. This feedback effect between educational attainment and wage distribution is not incorporated in this exercise.

These distributional interactive effects cannot be measured in the simple exercise done in this paper. More careful study, such as micro-simulation that incorporates the feedback effect from the education profile to wage level, is required. Studies like Bourguignon, Ferreira and Lustig (2004) or Vos and De Jong (2003) suggest a micro-simulation approach to analyze the effects of shocks on the job status and remuneration of individual workers and thereby on household income distribution and poverty.

[13] As the cutoff increases from .3 to .5, the projected value varies from 3.1% to 2.1% for the total sample, and from 3.5% to 2.1% for the male only sample.

5. Conclusion

This paper studies the impact of climate events on educational attainment. Instead of using multiple number of cross section or panel data sets, the educational attainment by age group in a single cross section data set is used to estimate the impact of historical climate shocks that might have affected people when they were school age children. The methodology used in this paper is applicable for many developing countries where detailed micro level panel data is scarce. While the approach may require additional work to explore specific requirement for an analysis with acceptable robustness, it could add value to the analyses of climate change and its impact on human development.

The main empirical finding from Cameroon, Burkina Faso, and Mongolia data sets suggest that extreme climate events have long term negative impact on the educational attainment. In Cameroon, women who might have been affected by a drought are 8.7 percentage point less likely to complete primary school. In Burkina Faso, the drought reduced the probability for women to finish primary school by 1.9 percentage point, but the result is not statistically robust due to the low average in primary school completion. In Mongolia, the wild fire reduced the probability for individuals to complete secondary school by 14.4 percentage point.

This paper also presents a benchmark figure of welfare loss caused by the climate events. When the wage information is available at the individual level, the potential impact of disaster on the average wage can be estimated using the disaster information, the estimated relationship between the disaster and schooling, and the estimated correlation between schooling and wage. In Mongolia, if there had been no wild fire in 1996, or if there had been a policy that protected households from the negative impact of the natural disaster, the average wage per worker, per year would have been 2.7% higher. Although it is a very limited preliminary projection, it can be used as a simple forecast figure of how much the economy will be better off if extreme climate shocks are completed hedged.

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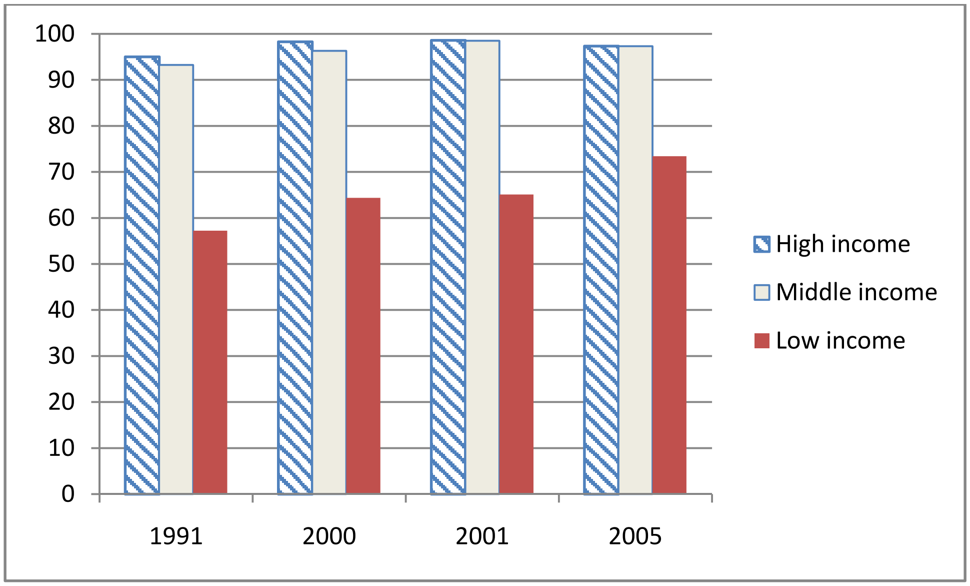
Figure 1 Primary completion rate (% of relevant age group)



Source: World Bank (2007)

Figure 2 Primary school enrolment rate from t_0 to t_1

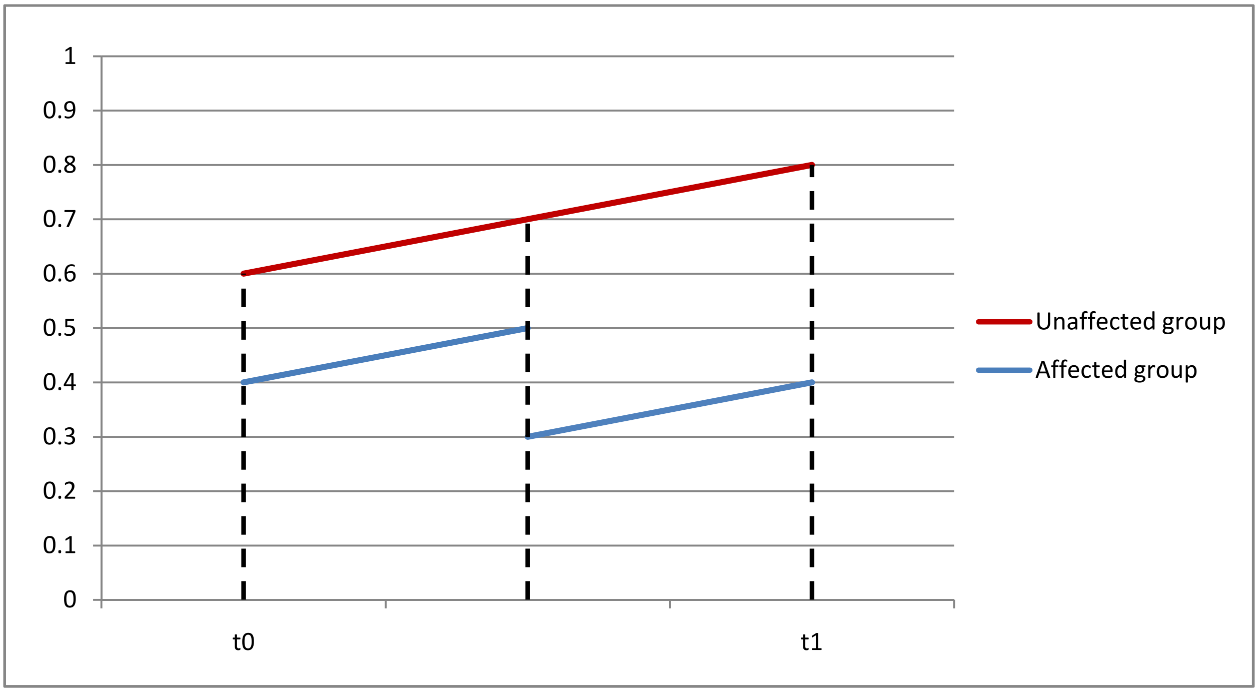


Figure 3 Primary school enrolment rate from t_{-7} to t_8

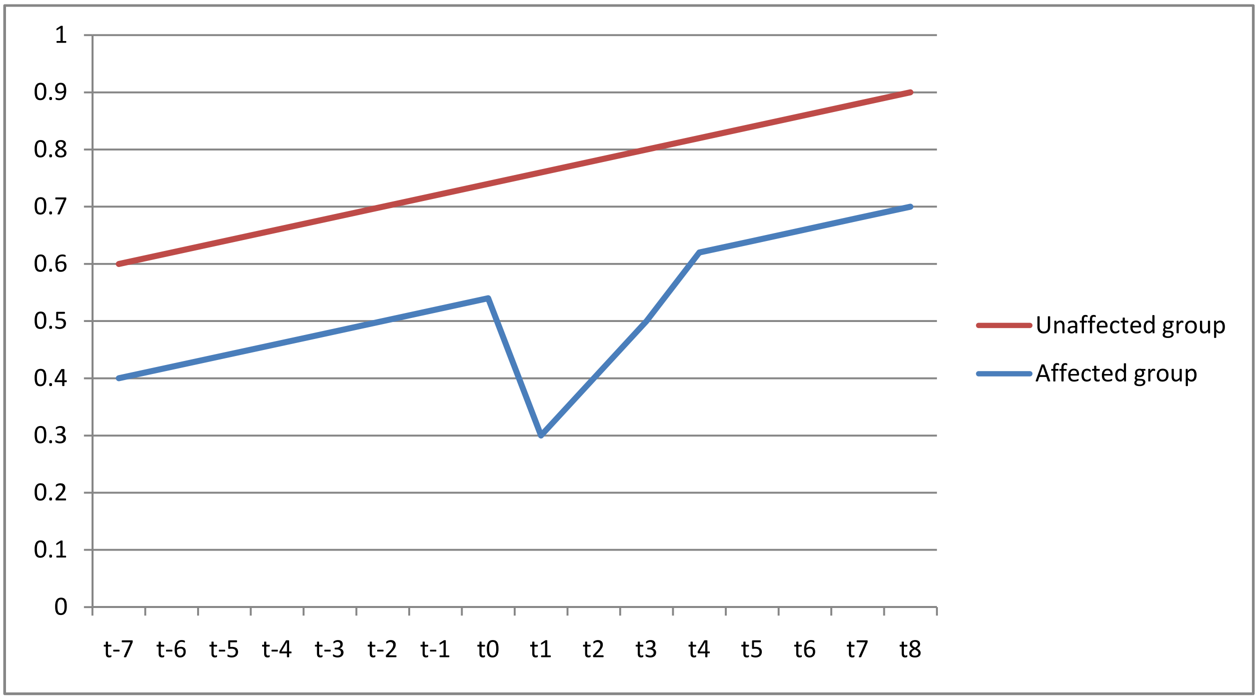


Figure 4 Primary school completion rate by age

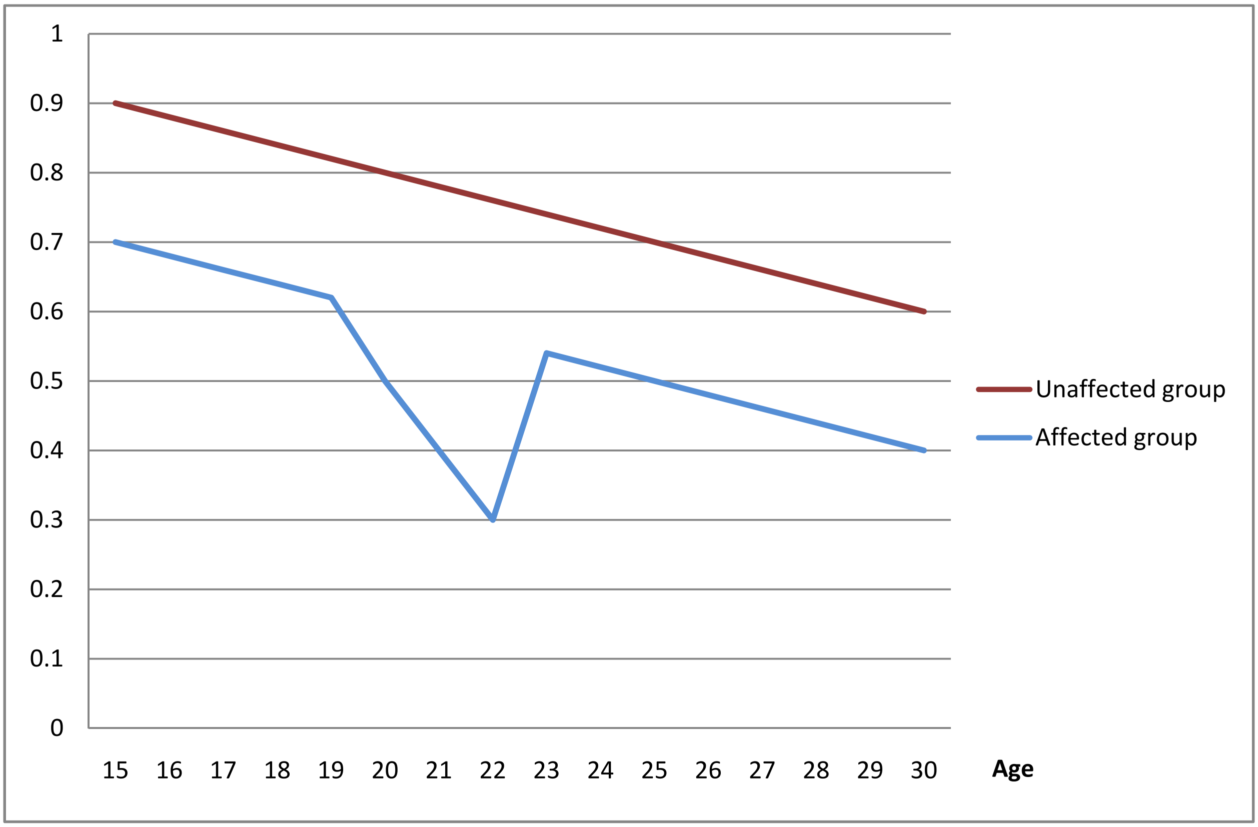


Table 1 Population that has attained at least upper secondary education (2004), Percentage, by age group

		Age group				
		Total	25-34	35-44	45-54	55-64
OECD COUNTRIES	Australia	64	77	65	62	49
	Austria	80	87	84	78	69
	Belgium	64	80	70	58	45
	Canada	84	91	88	83	73
	Czech Republic	89	94	93	87	82
	Denmark	81	86	82	79	77
	Finland	78	89	86	76	59
	France	65	80	70	59	49
	Germany	84	85	86	84	79
	Greece	56	73	64	50	31
	Hungary	75	84	82	76	57
	Iceland	60	68	64	57	46
	Ireland	63	79	68	54	39
	Italy	48	64	52	44	28
	Japan	84	94	94	82	65
	Korea	74	97	86	57	34
	Luxembourg	62	74	64	58	51
	Mexico	23	25	25	21	13
	Netherlands	71	80	74	68	59
	New Zealand	78	85	81	77	64
	Norway	88	96	92	86	78
	Poland	50	60	49	46	42
	Portugal	25	40	26	18	12
	Slovak Republic	85	94	91	84	64
	Spain	45	61	50	36	21
	Sweden	83	91	89	81	71
	Switzerland	85	89	86	83	79
	Turkey	26	33	24	20	14
	United Kingdom	65	70	65	64	59
	United States	88	87	88	90	86
	OECD average	**67**	**77**	**71**	**64**	**53**
PARTNER COUNTRIES	Brazil	30	38	32	27	11
	Chile	50	64	52	44	32
	Israel	79	86	81	75	68
	Russian Federation	89	92	95	90	72

Source: modified from OECD (2006). Table A1.2a

Table 2 Summary Statistics

Country	Cameroon	Burkina Faso	Mongolia
Data	DHS	DHS	LSMS
Year	2004	2003	2002
Number of observation	10,656 adult women	10,307 adult women	14,789 individuals
Primary school completion (average)	.65	.11	.96
Primary school completion (standard deviation)	.47	.31	.19
Secondary school completion (average)	.11	.03	.54
Secondary school completion (standard deviation)	.32	.18	.49

Table 3 School dropouts in Mongolia, 2002

Reason for leaving school		
	Not interested	35.1
	Parents not interested	9.8
	School too difficult	2.1
	Lack of budget	12.4
	Required to work	12.4
	Sick	13.7
	Required to look after others	4.2
	School too far	3.8
	Teachers not good	0.4
	Migration	0.8
	No place in school dormitory	1.2
	Too old	3.4
	Total	100
Would you like to go back to school		
	Yes	38.7
	No	61.3
Why not possible to go back to school		
	Parents not interested	3.4
	Lack of budget	49.9
	Not qualified	18.9
	Busy	10.3
	School too far	1.7
	Physically mentally disabled	1.7
	Sick	6.8
	Too old	1.7
	Other	5.1
	Total	100

Source: Mongolia LSMS 2002, author's calculation

Table 4 Probit regression results for Cameroon (2004), Burkina Faso (2003) and Mongolia (2002), Age under 35

	Cameroon	Burkina Faso	Mongolia
Dependent variable	Primary school completion	Primary school completion	Secondary school completion
Disaster			
Drought1990	-.0876* (.0490)		
Drought1988		-.0193 (.0262)	
Fire1996			-.1437** (.0513)
Other control			
Age	.0311** (.0099)	.0012 (.0092)	.1144** (.0166)
Age^2	-.0007** (.001)	-.0001 (.0001)	-.0018** (.0003)
Sex			-.1720** (.0161)
Number of observation	8261	7925	4673
R^2	.5197	.1869	.1335

Note: * significant at 5%. ** significant at 1%. Robust standard errors in brackets.

Table 5 Wage regression (Eq 2) and Loss of income (Eq 3), Mongolia 2002

Equation (2)[1]	All	Male only
Secondary education	.2498**	.2271**
	(.0309)	(.0427)
Age	.0179*	.0221*
	(.0070)	(.0101)
Age^2	-.0002*	-.0003*
	(.0000)	(.0001)
Constant	10.36**	10.41**
	(.1358)	(.1970)
Number of observation	2400	1137
R^2	.30	.37
Equation (3)[2]	$\overline{C}$ = .4	$\overline{C}$ = .4
Log (monthly wage)	10.94621	11.01804
Log (monthly wage) counterfactual	10.97284	11.04517
Wage, yearly in current US$	$613	$659
Wage, counterfactual, yearly in current US$	$630	$677
Loss of income (counterfactual wage-wage)	$17 (2.69%)	$18 (2.75%)

Note 1: * significant at 5%. ** significant at 1%. Robust standard errors in brackets.
Note 2: US$ values are calculated using official exchange rate in World Bank (2007).The wages are per year, per worker. The figures in parentheses are percentages relative to current wages.