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CLIMATE CHANGE AND POVERTY IN VIETNAM

Background Paper

Environmental Risks and Poverty

Analyzing Geo-Spatial and Household Data from Vietnam

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Abstract

This study combines high-resolution, geo-spatial data and household data from the Vietnam Living Standard Measurement Surveys in 2010, 2012, and 2014 to investigate the relationship between environmental risks and poverty. Using recently developed data on air pollution, tree cover loss, land degradation, slope, rainfall and temperature variability, and flood and drought hazards, the study shows: (i) at the district level, there are hotspots of high poverty and environmental risks; (ii) ethnic minorities and poor households are much more exposed to multiple environmental risks than other groups, and also within rural and urban

areas poorer households live in communes exposed to higher environmental risks; and (iii) environmental risks relate to lower consumption levels, but less so to lower consumption growth over time. Altogether these findings suggest that Vietnam's poor are disproportionately exposed to environmental risks, which can result in livelihood impacts that in many ways go beyond consumption. In light of growing pressures due to population growth, economic development and climate change, green growth actions, ecosystem-based adaptation, and land-use planning could be important strategies to reduce the environmental burden on poor people.

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Environmental Risks and Poverty: Analyzing Geo-Spatial and Household Data from Vietnam*

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1. Introduction

It has been claimed that environmental risks are a constraint to sustainable economic growth and lasting poverty reduction, especially in dynamically growing countries. Vietnam has experienced an average annual GDP growth of about 5.5 percent since 1990 and reduced extreme poverty from around 60 percent in 1990 to 13.5 percent as of 2014 (World Bank Group, 2016).¹ Nevertheless, pockets of poverty still exist today: 91 percent of people in extreme poverty live in rural areas and belong to marginal groups, such as ethnic minorities, who have a poverty rate of about 58 percent (Kozel, 2014).

At the same time Vietnam is facing various environmental challenges. Land is increasingly degraded by human-induced factors (Vu et al., 2014a, Vu et al., 2014b). Although total tree cover has increased, certain areas suffer from high rates of natural forest loss and forest degradation (Pham et al., 2012). Satellite data suggest that air pollution is increasing to high levels (World Bank Group, 2016). At the same time weather variability and extreme events, such as floods and droughts, severely affect livelihoods (Arouri et al., 2015; Bui et al., 2014; Narloch, 2016; Thomas et al., 2010). All of these risks could be exacerbated by population growth, unmanaged development and climate change.

These interlinkages between poverty and environmental risks could be mutually-reinforcing - often referred to as the environment-poverty nexus (Reardon and Vosti, 1995). Due to the lack of other opportunities, many of the poor live in high risk areas where they are more exposed to hazards and are more vulnerable to any negative impacts (Hallegatte et al., 2016). Many of them also overly depend on ecosystems and natural resources for income generation (as shown for Vietnam in Narloch, 2016) and to cope with shocks (Angelsen et al., 2014; Barbier, 2010; Wunder et al., 2014). On the one hand, being exposed to environmental risks forces poor people to opt for lower-risk, but lower-return strategies, which can make it harder to escape poverty. On the other hand, the dependence on natural resources can increase ecosystem fragility and environmental risks. This downward spiral could result in poverty traps (Barbier, 2010; Barrett et al., 2011; Carter et al., 2007).

Environmental risks are unevenly distributed across space – depending on geographic and climate conditions, as well as socioeconomic factors that condition them. Moreover, poor people are often concentrated in remote and disadvantaged areas, as for example the mountain areas in Vietnam. Such conditions could result in spatial poverty traps through geographic pockets of fragility, risks, marginalization and poverty (Barbier, 2012). An earlier spatial analysis at the provincial level, however, finds that the relationship between poverty and environmental risks is hard to generalize in Vietnam (Dasgupta et al., 2005).

This paper revisits this relationship, taking advantage of recent data, which allow the analyses of spatial relationships between environmental risks and poverty and consumption changes over time. First, the paper uses high-resolution data representing environmental risks across space. These data are combined with national maps showing the incidence of poverty at the district level (Lanjouw et al., 2013). In addition, this study computes environmental risks at the commune level² to relate it to household information based on the Vietnam Household Living Standard Surveys (VHLSS) for 2010, 2012, and 2014. Benefiting from the panel

¹ This number is based on the national poverty line, which is at is \$3.49-a-day in 2011 PPP terms. By the \$1.90-a-day poverty line, the extreme poverty rate was 3% in 2014.

² These are third-level administrative subdivisions, equivalent to a sub-district.

structure of these surveys, which includes half of the 9,400 households interviewed in at least two of the three rounds, we assess how environmental risks are related to consumption differences between households and consumption changes over time.

A number of recently-developed data sets are used to assess 8 environmental risks: (i) outdoor air pollution as a proxy for health risks through respiratory diseases (from Brauer et al., 2015); (ii) tree cover loss as a proxy for the loss of forest resources and ecosystem function (from Hansen et al., 2013); (iii) land degradation as a proxy for productivity decline and agricultural production risks (from Vu et al., 2014b); (iv) slope as a proxy for fragile environments vulnerable to erosion and landslides (from World Soil Database); (v-vi) long-term rainfall and temperature variability as a proxy for the variation of weather conditions (from the Climate Research Unit (CRU)); (vii) flood hazards as a proxy for the risks of being flooded (from Bangalore et al., 2016); and (viii) drought hazards as a proxy risks to become affected by drought events (from Winsemius et al., 2015).

Based on these data, the paper addresses three questions: (1) Are there spatial hotspots of high environmental risks and high poverty incidence? (2) Do poorer households live in communes with higher environmental risks? (3) Do environmental risks relate to consumption differences between households and consumption changes over time? These analyses are complementary to other recent work for Vietnam analyzing the income effects of current weather shocks (Narloch, 2016) and the exposure of poor people to future flood risks under different climate change scenarios (Bangalore et al., 2016).

The remainder of this paper is structured as follows. Section 2 describes the data used in the analyses. Section 3 shows the district-level overlay of environmental risks and poverty in 2010. Section 4 compares environmental risks at the commune level across household groups and urban and rural areas. Section 5 deepens these analyses by presenting results from various regression models explaining consumption differences between households and changes over time by environmental risks at the commune level. Section 6 concludes.

2. Data

This study combines household data from the Living Standard Measurement Surveys, VHLSS 2010, 2012, and 2014, and recent geo-spatial data measuring environmental risks at the district and commune levels.

2.1 Socioeconomic data

The study mainly relies on household data from the VHLSS 2010, 2012, and 2014. These surveys are conducted by the General Statistics Office (GSO) with technical support from the World Bank in Vietnam. They are nationally and regionally representative and contain detailed information on individuals, households and communes. In total 9,400 households nationwide are included in each round. Half of these households were also interviewed in the previous round so that the data set includes a short-term panel.

The VHLSS provide detailed information to estimate consumption expenditure, which can be used to estimate poverty rates. This study uses district-level poverty maps based on estimates from the VHLSS 2010 combined

with the 15-percent sample of the 2009 Population and Housing Census as calculated by Lanjouw et al. (2013). In addition, household consumption is calculated from the VHLSS 2010, 2012, and 2014 based on detailed expenditure data in line with the methodology for determining the GSO-World Bank poverty line. All consumption values are expressed in 2011 Purchasing Power Parity (PPP) values using data on the Consumer Price Index from the World Development Indicators.

These consumption estimates are used for the household-level analyses differentiating between different socioeconomic groups and rural and urban areas. In rural areas 6,600-6,750 households from about 2,200 communes in each year are included ('Pooled' cross section), 1,400 of them observed in all three rounds, 1,600 of them in 2010 and 2012, and 1,400 in 2012 and 2014 ('Panel' data set). In urban areas, the data set covers 2,650-2,780 households in each year from 900 communes ('Pooled'), 500 of them in all three rounds, 575 in 2010 and 2012, and 640 in 2012 and 2014 ('Panel').

The household and commune surveys in the VHLSS 2010, 2012, and 2014 also include a wide array of data on socioeconomic conditions. Data at the individual-level include demographics, education, employment, health, and migration. At the household-level data comprise information on durables, assets, production, income, and participation in government programs. The commune surveys collect information about the commune characteristics including access to land, infrastructure and services. Based on these data a number of socioeconomic controls are constructed for the analyses based on household and commune surveys (the summary statistics can be found in Table A.1).

2.2 Environmental risk data

Based on geo-spatial data sets, variables are constructed to measure environmental risk at district and commune levels representing 8 environmental risks. These variables are based on historical risk profiles measuring the area's exposure to fragile and severe conditions and not the actual environmental conditions at the time of the VHLSS surveys. The following variables are calculated to measure environmental risks at the district and commune levels (the summary statistics can be found in Table A.1):

1) Air pollution is measured by the area-weighted mean of concentration (measured as micrograms per cubic meter) of particulate matter with a diameter of 2.5 micrometers or less (PM2.5) taking the 10 years-average value for 2000-2010. The data is based on satellite imagery using the total column aerosol optical depth from the Moderate Resolution Imaging Spectroradiometer (MODIS) and Multiangle Imaging Spectroradiometer satellite instruments, which is combined with chemical transport model simulations, and ground measurements from 79 countries to produce a global spatial data set with $0.1^\circ \times 0.1^\circ$ resolution (Brauer et al., 2015). PM2.5 includes dust, dirt, soot, smoke, and liquid droplets, which can lodge deeply into the lungs due to their small size. PM2.5 air pollution has been identified as a leading risk factor for global diseases (Forouzanfar et al., 2015).

2) Tree cover loss is calculated as the share of the area under tree cover in 2000 that suffered from a tree cover loss between 2000 and 2010. Tree cover is defined as canopy closure for all vegetation taller than 5m in height and is calculated from imagery from the Landsat 4, 5, 7, and 8 satellite data used to produce a global

forest cover change map (Hansen et al., 2013). Tree cover loss can be associated with a habitat disturbance and ecosystem service disruptions, which can make human landscapes more fragile to other impacts (Sodhi et al., 2010). And it can also undermine the livelihoods of poor people highly dependent on forest timber and other resources (Angelsen et al., 2014).

3) Land degradation is measured by the share of land area that experienced a significant biomass decline. This loss is calculated based on the inter-annual mean trend of Normalized Difference Vegetation Index based on data from Advanced Very High Resolution Radiometer (AVHRR) of the National Oceanic and Atmospheric Administration (NOAA) satellite between 1982 and 2006, which is corrected for climate effects to only measure human-induced degradation (Vu et al., 2014b). Soil fertility, agricultural productivity and ultimately food security of smallholder farmers can be largely compromised on degraded lands (Von Braun et al., 2013).

4) Slope is measured by the area weighted average of slope categories. This variable is calculated based on data from the Harmonized World Soil Database version 1.2 with eight slope classes: 1 for least steep (elevation of 0-0.5 percent) and 8 for most steep slope (elevation greater than 45 percent).³ Steep slopes are much more prone to surface water runoff and soil erosion - particularly in areas affected by heavy rainfalls and tree cover loss (Sidle et al., 2006; Vezina et al., 2006). At the same time tropical cyclones can cause fatal landslides, which already result in significant loss of life in mountainous areas of South and East Asia (Petley, 2012, Petley, 2010).

5) Rainfall variability is defined as the 1981-2010 standard deviation of monthly rainfall levels. The variable is constructed from the global CRU TS3.21 dataset from the University of East Anglia, containing a long-term time series of monthly rainfall levels at 0.5x0.5 grid resolution, which was produced using statistical interpolation based on data from 4,000 weather stations (Harris et al., 2014). Higher historic rainfall variability indicates higher inter-annual and intra-annual variation of precipitation and a higher incidence of extremely wet and dry conditions. In Vietnam excessive rainfall can have negative income effects for poor households, while wealthier households are more negatively affected by the lack of rainfall (Narloch, 2016).

6) Temperature variability is measured by the standard deviation of mean annual temperatures across the time period 1981-2010. The underlying data also comes from the global CRU TS3.21 dataset including a long-term time series of monthly mean temperature values at 0.5x0.5 grid resolution. Temperature variability indicates varying temperature conditions between seasons and years and a higher incidence of heat waves and cold spells. In Vietnam hot conditions have generally an income-reducing effect for rural households (Narloch, 2016).

7) Flood hazards are represented by the share of area at risk of a flood event (inundation depth > 0) with a 25 year return period under historical conditions.⁴ The measures are based on the inundation depth estimated by state-of-the art flood models at a grid cell level of 3 arc-seconds combining coastal surge hazard

³ <http://www.fao.org/soils-portal/soil-survey/soil-maps-and-databases/harmonized-world-soil-database-v12/en/>

⁴ A 25 year return period corresponds to 0.04 annual probability of occurrence.

layers, along with pluvial and fluvial layers (Bangalore et al., 2016). In Vietnam flood events have been shown to significantly reduce welfare and increase poverty (Arouri et al., 2015; Bui et al., 2014; Thomas et al., 2010).

8) Drought hazards are measured by the intensity of drought conditions. This intensity is expressed by the number of months of long-term mean discharge which would be needed to overcome the maximum accumulated deficit volume during dry months (Winsemius et al., 2015). Drought events in Vietnam are associated with agricultural production losses, negative welfare impacts and poverty (Arouri et al., 2015; Bui et al., 2014; Thomas et al., 2010).

There are two main limitations of these variables for the purpose of this study. All these variables are time-invariant (i.e. have the same value for all the years with household survey data) as they are based on historic risk profiles. On the one hand, it would be preferable to measure actual conditions during the survey years to control for any changes between the years, which is not possible with the available data sets. On the other hand, measuring environmental risks based on past conditions minimizes causality problems, whereby consumption and income can determine current environmental conditions. However, the data cannot address any omitted variables bias, which leads to some endogeneity concerns (as will be discussed in section 5). Moreover, most of these variables are based on global data sets using global models or data, which are not necessarily representative for the specific conditions within the districts and communes in Vietnam. Optimally such variables would be measured based on ground station data, which however is not readily available. Although these are important limitations that require further work, the available data can provide some first insights into the relationships between environmental risks and poverty.

3. Environmental risks and poverty across districts

This section performs a spatial analysis to explore whether the incidence of poverty is higher in districts with high environmental risk levels.

3.1 Methods

National maps are produced that show the extent of environmental risks and poverty at district-level. First, all environmental risk variables are calculated at district level and all districts are then categorized into three groups with an equal number of districts in each group: high, medium and low risks.⁵ Similarly, all districts are classified into high-medium-low poverty categories based on the 2010 poverty rate maps produced by Lanjouw et al. (2013). In addition, we calculate the absolute number of poor people in each district, also from Lanjouw et al. (2013) and classify districts as high, medium and low poverty according to the number of poor people. These relative and absolute poverty maps are then overlaid with the environmental risk maps (Figures 1 and A.1). In addition, the poverty rate and number of poor people in each risk category is calculated (Tables 1 and 2).

⁵ For land degradation, due to the large number of districts experiencing no loss (0), the low risk category includes all districts with 0 loss (243 districts), and the rest of the districts are split into the medium and high categories.

3.2 Results

There is considerable spatial variation in poverty and environmental risks across Vietnam. As is indicated by the dark red districts in Figure 1, the incidence of poverty is highest in the Northern Mountains and in the Central provinces. The dark blue districts in Figure 1 suggest that air pollution and temperature variability are highest in the Northern districts. The Northwest region and Central Highlands face high tree cover loss and steep slopes, while the Central Coastal zones, the Red River and Mekong River Deltas face high rainfall variability and flood hazards. Areas with high land degradation and flood hazards appear across the country - mostly in the Northwest and Southeast region and the Mekong River Delta. These findings suggest that some areas face various risks so that their populations are exposed to multiple hazards.

Across Vietnam there are some large hotspots of high environmental risks and poverty. As indicated by the dark districts in the maps (Figure 1), Northern districts face a combination of high poverty and high air pollution, tree cover loss, steep slopes, temperature variability and drought hazards. In the Central Highlands, tree cover loss, steep slopes and rainfall variability pose high risks on poorer districts. And in the Mekong River Delta there are a few poorer districts that face high land degradation, flood and drought hazards. When looking at absolute poverty numbers, a few shifts in these patterns emerge from sparsely populated districts, as for example, in the Central Highlands, to districts with larger concentrations of poor people (Figure A.1).

Generally, in high risk districts the poverty rate is higher than in low risk districts. The difference is most pronounced for tree cover loss and slope, but also significant for all the other environmental risks (Table 1). Only for flood hazards, poverty is significantly higher in low risk districts than in high risk districts. This observation can be explained with the higher incidence of flood hazards in prosperous coastal regions and river deltas (Figure 1, also see Bangalore et al., 2016).

Similarly, a high number of people below the poverty line are concentrated in high risk areas. And the number of poor people is significantly higher in high risk than in low risk areas, with an average of about 30,000 people living in districts with high tree cover loss and land degradation, steep slopes and large drought hazards (compared to 20,000 people in low risk districts) (Table 2). And even an average of 20,000 people live in districts with high flood hazards, implying that floods can still affect a high number of poor people, even though they affect relatively wealthier districts.

Table 1 *Poverty headcount across environmental risk categories at district-level*

Risk category	Air pollution	Tree cover loss	Land degradation	Slope	Rainfall Variability	Temperature Variability	Flood hazards	Drought hazards
Low	21.3%	13.5%	19.5%	14.6%	20.6%	18.0%	49.1%	21.4%
Medium	33.2%	29.1%	32.6%	16.8%	35.6%	32.2%	16.7%	28.3%
High	26.9%	38.6%	30.0%	49.7%	25.5%	31.5%	15.4%	31.6%
ANOVA								
F	16.83	92.14	24.11	361.41	28.49	31.56	322.54	12.71
Prob>F	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Notes: Table shows the poverty headcount rate across the three environmental risks categories as calculated for Figure 1 and statistics from a one-way analysis-of-variance (ANOVA).

Source: Authors' calculation based on data from Brauer et al., 2015, Hansen et al., 2013, Vu et al., 2014b, Harmonized World Soil Database, Climate Research Unit, Bangalore et al., 2016, Winsemius et al., 2015, and Lanjouw et al., 2013.

Figure 1 *Overlay of poverty rate and environmental risk categories at district-level*

a. Air pollution

c. Land degradation

e. Rainfall variability

Flood hazards

b. Tree cover loss

d. Slope

f. Temperature variability

Drought hazards

Notes: Figures the district-level overlay of poverty and environmental risks maps based on the following categories (calculated as three terciles, with equal number of districts in each category): Poverty - Low = <14%, Medium = 14-28%, High = >28% based on poverty headcount; Air pollution - Low = < 9.11 , Medium = 9.11-23.75 High = >23.75 based on area-weighted PM2.5 pollution levels (micrograms per cubic meter); Tree cover loss - < 0.21 , Medium = 0.21-2.28 High = >2.28 based on share of forest area affected by tree cover loss; Land degradation - Low = 0, Medium = 0.01-20.14 High = >20.14 based on area share affected by biomass loss; Slope - Low = < 2.7, Medium = 2.7-5.3 High = >5.3 based on area-weighted average of slope category; Rainfall variability - < 45.50, Medium = 45.50-61.44 High = >61.44 based on the long-term standard deviation of monthly rainfall; Temperature variability - < 0.61, Medium = 0.61-0.85 High = >0.85 based on based on the long-term standard deviation of monthly mean temperature; Flood hazards: Low = <10%, Medium = 10-30%, High = 30%> based on the area shared at risk of a 25-year return period flood; Drought hazards: - < 0.87, Medium = 0.87-1.04 High = >1.04 based on number of months to overcome water deficit during dry months.

Source: Authors' calculation based on data from Brauer et al., 2015, Hansen et al., 2013, Vu et al., 2014b, Harmonized World Soil Database, Climate Research Unit, Bangalore et al., 2016, Winsemius et al., 2015, and Lanjouw et al., 2013.

Table 2 *Number of poor people across environmental risk categories at district-level*

Risk category	Air pollution	Tree cover loss	Land degradation	Slope	Rainfall Variability	Temperature Variability	Flood hazards	Drought hazards
Low	23,393	19,792	18,206	21,302	22,117	21,688	30,318	20,172
Medium	24,874	25,046	27,650	21,858	28,054	27,455	21,769	24,281
High	25,741	28,967	28,713	30,632	24,106	25,124	21,704	29,349
ANOVA								
F	1.08	16.99	28.63	22.27	7.09	6.56	19.82	16.94
Prob>F	0.3405	0.0000	0.0000	0.0000	0.0009	0.0015	0.0000	0.0000

Notes: Table shows the number of poor people across the three environmental risks categories as calculated for Figure A.1 and statistics from a one-way analysis-of-variance (ANOVA).

Source: Authors' calculation based on data from Brauer et al., 2015, Hansen et al., 2013, Vu et al., 2014, Harmonized World Soil Database, Climate Research Unit, Bangalore et al., 2016, Winsemius et al., 2015, Lanjouw et al., 2013 and Geographic Information Science and Technology, 2015.

4. Commune-level environmental risks across household groups

This section explores whether poorer households, as measured by consumption expenditure, live in communes with higher levels of environmental risks based on descriptive statistics and nonparametric analyses.

4.1 Methods

To compare environmental risks across households, the level of environmental risks is calculated for each commune. Whereas the geographical location of communes is known, the household data from the VHLSS is not geo-coded so that it is not possible to track the exact location of households within communes. Although there can be considerable variation in environmental conditions within communes, environmental risks measured at commune level can measure the wider risk environment the household is exposed too.⁷ For each commune, the area-weighted average of the high-resolution environmental variables is calculated,⁸ as explained in section 2.2. Also the standardized value of each environmental risk is calculated by subtracting from each commune value the mean and dividing by the standard deviation, producing a value distribution with the mean of 0 and a standard deviation of 1. Such normalization produces a scaled version of the original value which allows comparison between the different risk variables.

Descriptive statistics and non-parametric analyses are conducted. First, the mean risk level is calculated for different household groups in each survey year, differentiating between consumption quintiles, households below the national poverty line, ethnic minorities and female-headed households (Figures 2 and A.2 for the standardized values and Table A.2 for the absolute values). Households are then divided into consumption percentiles based on the expenditure data from the VHLSS and split into a rural and urban subsamples for each

⁷ Furthermore, as communes are about a fifth of the size of districts, there is likely to be considerably less variation in environmental risk within communes than within districts.

⁸ For the weather and temperature variability, due to the coarse resolution of the data, the value that the centroid of the commune is taken to represent these risks (rather than the area-weighted average).

year. For each of these consumption quintiles, the mean level of environmental risks is calculated and shown in binned scatterplots, which also plot fit lines (Figure 3, and A.3-A4).

4.2 Results

At the national level, marginalized and vulnerable groups are more exposed to multiple environmental risks. Ethnic minorities and households below the poverty line have the highest risk exposure, while households in higher consumption quintiles and those headed by females live in less risky communes (Figure 2). Ethnic minorities and poor households have similar risk profiles, also because more than 50 percent of poor households belong to ethnic minorities. In particular, risks from air pollution, tree cover loss, land degradation, steeper slopes and droughts are higher for them. Compared to other groups, however, they face lower flood hazards (see discussion below). For most environmental risks the differences between groups are significant (Table A.1). These risk profiles are very similar over time indicating that the spatial mobility of these groups between 2010 and 2014 have been low with limited movement out of high risk zones (Figure A.2).

Figure 2 *Environmental risk profiles across socio-economic groups 2014*

Source: Authors' calculation based on data from Brauer et al, 2015, Hansen et al., 2013, Vu et al. 2014b, Harmonized World Soil Database, Climate Research Unit, Bangalore et al., 2016, Winsemius et al., 2015, and VHLSS 2014.

Also within urban and rural areas, poorer households tend to live in communes with higher environmental risks. In rural areas they are more exposed to air pollution, tree cover loss, steep slopes, rainfall and temperature variability, but less exposed to flood hazards (Figure 3). The latter finding could reflect that many of the rural poor live in the mountainous areas where flood hazards are generally lower than in low-lying, but wealthier river deltas and coastal zones. In urban areas, poorer households are more concentrated in areas with high tree cover loss, slope, flood and drought hazards, while living in places with lower air pollution and temperature variability. Possibly, wealthier households live in rapidly developing urban areas with heavy traffic and industrial congestion, thereby being more exposed to air pollution.

Some remarkable differences in risk exposure of poor people appear between urban and rural areas (Figure 3). First of all, poor rural households are much more concentrated on steep slopes and areas with high air pollution and temperature variability than their urban counterparts indicating that in rural areas poor people could have a higher exposure to multiple, interlinked risk factors. For floods, however, a different picture emerges, as flood hazards seem to be more a problem for poor urban households than poor rural households. This finding is consistent with a recent global analysis of flood exposure and poverty in 52 countries, which reports ambivalent results for flood exposure at the country level, but shows a strong signal of over-exposure of the poor when only focusing in urban areas (Winsemius et al., 2015).

While most of these relationships hold over time, some differences can be observed in 2010 and 2012 in rural areas (Figure A.2). In 2014 there is no considerable relationship between consumption and land degradation, while in 2012 and even more so in 2010, poorer households have a higher exposure to land degradation. This change over time could imply that people in highly degraded areas have become wealthier over time, a finding that is also reflected in the results of the next section. The U-form relationship between consumption and air pollution and temperature variability in 2010 changes to a strongly negative relationship in 2014 suggesting that over time wealthier households could become more concentrated in low risk areas.

Figure 3 *Environmental risks across consumption percentiles in rural and urban zones, 2014*

Notes: Binned scatterplots show the non-parametric relationship between consumption and environmental risks. X-axis shows percentiles of natural logarithm of per-capita expenditure in 2014. Y-axis indicates level of environmental risks.

Source: Authors' calculation based on data from Brauer et al, 2015, Hansen et al., 2013, Vu et al., 2014b, Harmonized World Soil Database, Climate Research Unit, Bangalore et al., 2016, Winsemius et al., 2015, and VHLSS 2014.

5. Environmental risks and consumption differences

This section investigates how environmental risks relate to consumption differences between households and consumption changes over time, applying a set of regression models.

5.1 Methods

Two sets of regression models are fitted to estimate risk impacts on consumption differences between households in the ‘Pooled’ cross-section and on consumption changes over time for the ‘Panel’ data set. A particularity of the VHLSS data is that, for some households, information is available for two or three survey years. These households form the *Panel* data set to explain consumption changes over time. Other households were only observed in one of the three years. Using these cross-section data, treating all observations as independent observations provides a *Pooled* data set to explain consumption differences between households.

Using Ordinary Least Squares (OLS) estimators the following equation is fitted in the *Pooled* and *Panel* models:

$$Y_{i,t} = \alpha + \beta R_j + \delta Z_j + \omega W_{j,t} + \gamma X_{i,t} + \lambda T_t + u_{i,t}$$

where Y denotes per-capita consumption observed for household i in commune j in year t (i.e. 2010, 2012, 2014) in the *Pooled* model and the change in per-capita consumption for household i between years t (i.e. 2010-2012 and 2012-2014) in the *Panel* model. R measures the environmental risk profile in commune j , which is time-invariant, as described in Section 2.2. β is the parameter of interest that indicates the consumption effect of environmental risks. Z includes commune-specific geo-spatial controls that do not change over time, such as proximity to cities and roads and the long-term average of rainfall and temperature. W includes a set of time-variant commune variables measured by rainfall and temperature levels in the survey years 2010, 2012 and 2014 for the *Pooled* model and by the change for 2010-12 and 2012-14 for the *Panel* model. X is a set of household-specific controls that vary over time, such the levels of education, labor and land endowments in survey years for the *Pooled* model and the difference between years for the *Panel* model. X also includes time-invariant demographic characteristics, such ethnicity and gender.⁹ T measures time-fixed effects to neutralize common trends over time. U is a random, idiosyncratic error term. The descriptive statistics of these variables are provided in Table A.1.

A main concern when fitting models to estimate weather impacts on economic outcomes is endogeneity bias. Problems of reverse causation (e.g. high consumption growth in one place leading to environmental depletion) are minimized by taking the historic risk profile and not measuring actual environmental conditions. Yet the model is likely to suffer from omitted variable bias caused by the potential correlation of risk variables with other commune characteristics that determine living standards. Such omitted variable bias could be minimized by fitting a fixed-effects linear model using a within-regression estimator based on the Panel data set as in Narloch (2016). Yet such a model does not allow to disentangle the impact of time-invariant risk factors so it cannot be applied for the purpose of this study. To minimize omitted variable bias in this study, a set of

⁹ The data sets allow to control for land and labor inputs of some activities. These are, however, not included in the regression analyses due to potential endogeneity biases, as higher risks also determines land and labor inputs.

observable commune characteristics is included that are likely to influence risk profiles and living standards, such as average rainfall and temperature conditions and distance from cities and roads. Nonetheless, to the extent that other, non-observable commune characteristics also determine risks and consumption, the estimates of β will be biased.

These regression models are estimated for various sub-samples to disentangle differences different groups, zones and years. For both the *Pooled* and *Panel* models, we first estimate the consumption effect one by one and then include all risk variables altogether. Robust standard errors are estimated by clustering at the commune-level in order to account for spatial correlation. For the *Pooled* model the natural logarithm of per-capita consumption is used in the regression to normalize the skewed distribution of consumption (i.e. many observations of low consumption levels and a few observations of very high consumption levels).¹⁰

5.2 Results

Environmental risks contribute to consumption differences between households. Across all households from the Pooled cross-section, those households, who live in communes with steeper slope, higher rainfall and temperature variability and flood and drought hazards have significantly lower consumption (Table 3 – All). Only for land degradation there seems to be a positive relationship, which may indicate communes of intensive agricultural expansion and growth, which could be positively associated to wealth in the short term. This finding points at the possible estimation biases from unobservable factors, which do not allow to establish clear causal relationships with these data.

Within the various groups different risk factors matter for consumption levels. As differences in per-capita expenditure between households below the poverty line are modest, it is not surprising that generally fewer variables are significant for the sub-sample of poor households and that the models have a much lower explanatory power (Table 3 – Poor). The role of environmental risks in explaining consumption differences for households in the lowest two consumption quintiles follow the overall pattern, but there is a significant positive relationship with air pollution (Table 3 – B40). The same finding emerges from the rural subsample (Table 3 – Rural). Possibly rural households in communes closer to urban zones are wealthier, while being more exposed to air pollution than their counterparts in remote rural areas. Whereas in rural areas slope, rainfall and temperature variability and droughts are negatively related to consumption, in urban areas floods have a significant negative effect (Table 3 – Urban). Very similar findings appear for the 2014 subsample, indicating that there are no considerable differences between the three survey years (Table 3– Urban 2014 and Rural 2014).¹¹

Changes in consumption over time are only related to a limited number of risk variables. Interestingly, households in communes with higher PM2.5 concentration levels have a significantly lower consumption growth (Table 4 – All). Temperature variability relates to a significantly higher consumption change mainly driven by urban households between 2012 and 2014 (Table 4 – Urban 2012-14). Among poor households those

¹⁰ Taking the natural logarithm also improves the explanatory power of the various models and brings ease in interpreting the coefficients as percentage change of the outcome variable.

¹¹ These results also hold when including the risk variables one-by-one and not the whole set.

living in communes with higher rainfall variability and drought hazards have a significantly lower consumption growth (Table 4 – Poor). For households within the lowest two consumption quintiles, floods seem to have a positive effect on consumption growth (Table 4 – B40). This finding may reflect that poorer households benefit from economic activities (e.g. floating rice) in floodplains, such as the Mekong River Delta. As long as no severe flood happened due to favorable weather conditions or protection measures, living in flood prone areas can result in higher incomes and welfare. When differentiating between rural and urban zones for both the 2010-12 and 2012-14 period many of the significant findings disappear (Table 4 – Rural and Urban). In line with the above finding for flood, higher land degradation is, however, positively related to consumption growth. Interestingly, lower consumption growth in 2012-14 is related to tree cover loss in rural zones and to rainfall variability in urban zones (Table 4 – Rural 2012-14 and Urban 2012-14).

Some interesting findings also appear from the results for the control variables (Tables 3 and 4). Higher levels of current rainfall and lower current temperatures are related to higher consumption levels and growth over time, which is broadly in line with the analyses in Narloch (2016).¹² While larger distance to cities and roads relate to lower consumption levels as would be expected, it is related to higher consumption growth over time – possibly indicating a catching-up of more remote communes. Having access to larger agricultural and water surface areas has a positive effect on both consumption levels and growth over time. Ethnic minorities have lower consumption levels and also experience lower consumption growth when compared to wealthier households. However, within the sub-samples of households below the poverty line and in the lowest two consumption quintiles, ethnic minorities have higher consumption growth.

The interpretation of these results should be seen with a note of caution. First of all, based on the available data, omitted variable bias could not be eliminated. As some of the findings suggest there may be some incidences in which being located in a high risk zone can also indicate other factors that explain living standards but cannot be controlled for with the available data. Furthermore, it is to be highlighted that some of the differences between the results from the *Pooled* and the *Panel* could be due to the different subsamples of households included in these analyses.

¹² One of the main differences is that the analyses in Narloch (2016) reduce omitted variable biases through fixed effects regressions.

Table 3 *Environmental risks as determinants of consumption differences between 'Pooled' households*

	Dependent variable: Ln of per-capita expenditure						
	All	Poor	B40	Rural	Rural 2014	Urban	Urban 2014
Air pollution	0.000511 (0.32)	0.00176 (1.01)	0.00255** (2.18)	0.00425*** (2.60)	0.00220 (1.14)	-0.00178 (-0.55)	-0.00315 (-0.81)
Tree cover loss	-0.00179 (-1.18)	0.00229 (1.60)	-0.00125 (-1.10)	0.00132 (0.88)	-0.00248 (-1.37)	-0.00705 (-1.35)	-0.00500 (-0.74)
Land degradation	0.000300* (1.87)	-0.000256 (-1.27)	0.000171 (1.26)	0.000108 (0.55)	0.000197 (0.81)	-0.0000844 (-0.33)	-0.00000728 (-0.02)
Slope	-0.0213*** (-3.98)	-0.0148** (-2.32)	-0.0102** (-2.43)	-0.0101* (-1.71)	-0.00389 (-0.55)	-0.0164 (-1.58)	-0.0117 (-0.88)
Rainfall variability	-0.00276*** (-4.48)	-0.00120 (-1.46)	-0.000420 (-0.75)	-0.00281*** (-4.21)	-0.00499*** (-4.73)	-0.000672 (-0.58)	-0.000577 (-0.33)
Temperature variability	-0.265* (-1.88)	0.0382 (0.22)	-0.212* (-1.68)	-0.454*** (-2.98)	-0.0311 (-0.17)	0.113 (0.42)	0.318 (0.95)
Flood hazard	-0.00144*** (-5.97)	-0.000202 (-0.74)	0.00000600 (0.04)	0.000183 (0.67)	0.000441 (1.43)	-0.00184*** (-4.05)	-0.00201*** (-3.96)
Drought hazard	-0.0335*** (-2.67)	0.00353 (0.26)	-0.0199** (-2.01)	-0.0428*** (-3.17)	-0.0379** (-2.29)	-0.0380 (-1.59)	-0.0477 (-1.56)
<u>Control variables</u>							
Current rainfall	0.00121*** (5.32)	0.000473* (1.68)	0.000247 (1.21)	0.00134*** (5.36)	0.00202*** (4.35)	0.0000388 (0.09)	0.000273 (0.30)
Current temperature	0.0322 (1.55)	-0.0504** (-2.20)	-0.0400** (-2.10)	0.00195 (0.09)	0.00123 (0.03)	0.0381 (0.97)	0.120 (1.45)
Long-term rainfall	-0.00191** (-2.37)	-0.000913 (-0.96)	-0.00109* (-1.66)	-0.00181** (-2.23)	-0.000495 (-0.49)	-0.000980 (-0.60)	-0.00148 (-0.68)
Long-term temperature	-0.0380* (-1.70)	0.0658*** (2.67)	0.0586*** (2.87)	0.00675 (0.28)	0.0270 (0.59)	-0.0321 (-0.78)	-0.0998 (-1.18)
Distance city	-0.00230*** (-7.79)	-0.000223 (-0.76)	-0.000399 (-1.63)	-0.00101*** (-3.32)	-0.000591 (-1.51)	-0.00253*** (-4.79)	-0.00220*** (-3.32)
Distance road	-0.0110*** (-6.29)	-0.00267** (-2.13)	-0.00462*** (-4.01)	-0.00832*** (-5.57)	-0.00785*** (-4.12)	0.00329 (0.62)	0.00618 (1.05)
Area agriculture	0.00153*** (2.93)	0.00130* (1.67)	0.00296*** (5.52)	0.00426*** (7.95)	0.00396*** (5.68)	-0.00169 (-1.24)	-0.000953 (-0.61)
Area forest	-0.00000525 (-0.05)	-0.000144** (-2.46)	-0.0000523 (-0.34)	0.0000935 (1.43)	-0.000213 (-0.49)	0.0000408 (0.01)	0.00505 (0.88)
Area water surface	0.00467*** (3.31)	0.00170 (1.02)	0.00272*** (2.81)	0.00432*** (3.21)	0.00753*** (5.16)	0.00517** (2.15)	0.00691 (1.03)
Workforce	-0.115*** (-10.90)	0.0910*** (6.69)	0.0735*** (8.39)	-0.00266 (-0.24)	0.00383 (0.25)	-0.168*** (-7.41)	-0.151*** (-4.56)
Education	0.103*** (63.51)	0.0243*** (10.75)	0.0375*** (23.50)	0.0860*** (49.28)	0.0849*** (33.60)	0.108*** (36.69)	0.105*** (23.40)
Age head	0.000656** (2.43)	0.000413 (1.34)	0.000315 (1.34)	0.000497 (1.64)	-0.0000227 (-0.05)	0.000576 (1.12)	0.00140* (1.91)
Female head	0.0854*** (9.56)	-0.00897 (-0.69)	0.00950 (1.11)	0.0684*** (6.36)	0.0673*** (4.37)	0.0399*** (2.74)	0.0303 (1.47)
Minority	-0.409*** (-24.35)	-0.0948*** (-6.11)	-0.228*** (-17.64)	-0.401*** (-22.16)	-0.429*** (-17.71)	-0.290*** (-7.87)	-0.346*** (-6.69)
Year 2012	0.0607*** (3.59)	-0.000678 (-0.03)	0.0835*** (5.33)	0.0558*** (3.02)		0.0660** (2.13)	
Year 2014	0.150*** (7.68)	-0.0142 (-0.57)	0.155*** (8.51)	0.147*** (6.99)		0.113*** (3.13)	
_cons	8.024*** (35.15)	6.487*** (25.99)	6.849*** (32.66)	7.513*** (30.26)	6.677*** (20.11)	7.580*** (18.23)	7.225*** (13.23)
N	27698	3811	11025	19748	6492	7950	2715
R-sq	0.432	0.204	0.365	0.399	0.409	0.316	0.305

Notes: Table indicates coefficients estimated from 'Pooled' Cross-section model using Ordinary Least Squares. * 0.10 ** 0.05 *** 0.01 significance level. Values in parentheses indicate standard errors corrected for cluster correlation at commune-level.

Source: Authors' calculation based on data from Brauer et al, 2015, Hansen et al., 2013, Vu et al., 2014b, Harmonized World Soil Database, Climate Research Unit, Bangalore et al., 2016, Winsemius et al., 2015, and VHLSS 2010, 2012 and 2014.

Table 4 *Environmental risks as determinants of consumption changes over time of 'Panel' households*

	Dependent variable: Change in per-capita expenditure						
	All	Poor	B40	Rural	Rural 2012-14	Urban	Urban 2012-14
Air pollution	-12.37* (-1.91)	6.040 (1.52)	-0.0273 (-0.01)	-4.189 (-0.86)	-3.224 (-0.42)	-34.10 (-1.58)	-41.43 (-1.61)
Tree cover loss	-4.166 (-0.73)	-1.376 (-0.40)	-5.865 (-1.63)	-4.605 (-0.83)	-13.16* (-1.92)	-0.818 (-0.03)	-5.808 (-0.11)
Land degradation	0.262 (0.33)	0.554 (0.96)	0.0442 (0.09)	1.555** (2.13)	0.542 (0.47)	-2.124 (-1.15)	-2.237 (-0.72)
Slope	8.262 (0.43)	-17.99 (-0.93)	4.052 (0.30)	-2.692 (-0.16)	-1.030 (-0.04)	38.90 (0.73)	67.10 (0.91)
Rainfall variability	-0.162 (-0.08)	-3.139* (-1.71)	0.445 (0.32)	-0.349 (-0.17)	-0.132 (-0.04)	-0.250 (-0.04)	-15.18* (-1.72)
Temperature variability	974.5* (1.74)	193.5 (0.61)	182.0 (0.67)	377.8 (0.88)	403.0 (0.63)	2582.1 (1.42)	6247.0** (2.40)
Flood hazard	-0.390 (-0.38)	0.110 (0.10)	1.533** (2.33)	-0.0430 (-0.05)	-0.602 (-0.45)	-4.244 (-1.30)	-3.479 (-0.99)
Drought hazard	-2.442 (-0.05)	-121.1** (-2.06)	-64.84 (-1.55)	-35.65 (-0.72)	53.63 (0.67)	137.7 (0.89)	58.11 (0.23)
<i>Control variables</i>							
Current rainfall	1.259 (1.09)	0.656 (0.89)	-0.458 (-0.66)	1.625 (1.59)	0.635 (0.40)	-0.560 (-0.16)	2.514 (0.50)
Current temperature	-190.0** (-2.20)	-37.60 (-0.57)	-48.73 (-0.90)	-103.5 (-1.32)	-40.98 (-0.22)	-406.5* (-1.69)	-239.6 (-0.46)
Long-term rainfall	1.080 (0.41)	5.660*** (2.69)	1.731 (1.03)	-0.469 (-0.20)	0.421 (0.10)	6.838 (0.85)	24.23* (1.89)
Long-term temperature	54.08** (2.48)	-44.43*** (-2.74)	9.712 (0.74)	25.99 (1.20)	59.33* (1.93)	109.1** (2.04)	226.8*** (2.85)
Distance city	2.372** (2.24)	0.965 (1.33)	1.647** (2.27)	1.450 (1.61)	1.915 (1.28)	3.100 (1.20)	0.678 (0.17)
Distance road	5.620 (1.15)	3.284 (1.13)	5.966** (1.97)	2.183 (0.49)	17.50*** (2.64)	15.10 (0.65)	13.03 (0.47)
Area agriculture	13.91*** (2.59)	8.732** (2.17)	14.39 (1.64)	12.56*** (2.62)	8.157** (2.24)	19.83 (1.09)	39.26* (1.93)
Area forest	0.336 (0.28)	0.146 (0.09)	0.155 (0.17)	0.315 (0.28)	0.209 (0.13)	22.92 (0.63)	35.49 (0.72)
Area water surface	25.81** (2.01)	24.64 (0.89)	11.20 (1.47)	33.36*** (3.80)	36.21*** (4.73)	-54.07 (-1.18)	-130.1 (-1.53)
Workforce	190.6*** (2.63)	166.7*** (2.82)	89.93** (2.17)	208.4*** (3.42)	228.1*** (2.72)	127.9 (0.44)	-489.4 (-1.08)
Education	117.4*** (5.75)	40.56 (1.40)	67.02*** (5.05)	73.88*** (4.26)	88.50*** (3.77)	235.3*** (4.02)	203.1*** (3.35)
Age head	-2.285 (-1.60)	-3.548*** (-3.09)	-2.276** (-2.53)	-1.553 (-1.14)	-4.078* (-1.94)	-4.467 (-1.18)	-5.595 (-0.95)
Female head	85.89 (1.52)	28.10 (0.64)	30.55 (0.91)	49.79 (1.03)	26.04 (0.33)	193.3 (1.44)	385.3* (1.94)
Minority	-152.8*** (-2.63)	175.7*** (3.27)	234.9*** (5.47)	-149.6** (-2.56)	-204.7** (-2.09)	-179.1 (-0.80)	-702.7** (-2.09)
Year 2012-14	139.8 (1.35)	-101.7 (-1.46)	-128.8** (-2.24)	96.08 (1.04)		202.4 (0.71)	
_cons	-1943.4** (-2.25)	188.1 (0.39)	-784.5* (-1.70)	-542.3 (-0.73)	-1461.6 (-1.38)	-5280.7** (-2.17)	-12451.3*** (-3.05)
N	7957	952	3250	5804	2792	2153	1109
R-sq	0.017	0.171	0.076	0.020	0.035	0.029	0.050

Notes: Table indicates coefficients estimated from 'Panel' model using Ordinary Least Squares and differences over time for time-variant variables. * 0.10 ** 0.05 *** 0.01 significance level. Values in parentheses indicate standard errors corrected for cluster correlation at commune-level.

Source: Authors' calculation based on data from Brauer et al, 2015, Hansen et al., 2013, Vu et al., 2014b, Harmonized World Soil Database, Climate Research Unit, Bangalore et al., 2016, Winsemius et al., 2015, and VHLSS 2010, 2012 and 2014.

6. Conclusions

This paper provides a novel analysis based on the combination of high-resolution, geo-spatial data and household data from Vietnam. Despite several limitations related to the available data sets, this study reveals the first empirical insights into the potential role of environmental risks in the livelihoods of poor people, using data sets that have become recently available and measuring a comprehensive set of environmental variables.

The findings show the following: (i) at district level there are large hotspots of high poverty and environmental risks; (ii) ethnic minorities and poor households are much more exposed to multiple environmental risks than other groups, and also within rural and urban zones poorer households live in communes exposed to higher environmental risks; and (iii) environmental risks relate to lower consumption levels, but less so to consumption changes over time. In particular, households in communes with steeper slopes and higher rainfall and temperature variability and greater flood and drought hazards have lower consumption levels, while those living in communes with higher air pollution have lower consumption growth. Although causal relationship between risks and consumption cannot be clearly established with the data, these findings suggest that poor people are disproportionately exposed to environmental risks.

More work is needed to confirm that environmental risks pose a threat to poverty eradication and shared prosperity. First, longer time-series data is needed to evaluate whether environmental conditions have long-lasting impacts on household living standards. Second, this study mostly relies on global data sets from remote sensing or modeling work, which needs to be verified and refined with monitored data at the subnational level – optimally from ground stations. Moreover, this study could only define historic risk profiles and not the actual environmental conditions and risk materialization within the survey years. The expansion of these analyses with such data will be an important area for deepening the findings of this work.

Even in the absence of such analyses, some evidence already exists that shows the detrimental impacts of environmental risks on poverty and household welfare. An accompanying study, for example, shows that actual variation in rainfall and temperature conditions is related to significant consumption and income effects also for poor people (Narloch, 2016). In addition, other work has shown the negative welfare and poverty impacts of flood and drought events (Aroui et al., 2015; Bui et al., 2014; Thomas et al., 2010). Moreover, poor people could be affected by environmental risks in many ways that go beyond income and consumption effects, such as detrimental health impacts or a decline in the quality of life due to poor environmental conditions. Such impacts cannot be measured with the existing household data.

In light of growing pressures due to population growth, economic development and climate change, environmental risks need to be considered in poverty reduction policies. Green growth actions that allow economic development without excessively harmful environmental impacts, for example through increased resource efficiency, will help to reduce the environmental burden on poor people. Moreover, ecosystem-based adaptation could strengthen ecosystem resilience and reduce environmental risks, while improving the livelihoods of people depending on these ecosystems. Carefully designed land-use planning policies that encourage resettlements and avoid new settlements in high risk areas are another key strategy to reduce exposure to environmental risks, but should be paired with investments in livelihood support and improved mobility.

References

- Angelsen, A., Jagger, P., Babigumira, R., Belcher, B., Hogarth, N.J., Bauch, S., Börner, J., Smith-Hall, C., Wunder, S., 2014. Environmental Income and Rural Livelihoods: A Global-Comparative Analysis. *World Dev., Forests, Livelihoods, and Conservation* 64, Supplement 1, S12–S28.
- Arouri, M., Nguyen, C., Youssef, A.B., 2015. Natural Disasters, Household Welfare, and Resilience: Evidence from Rural Vietnam. *World Dev.* 70, 59–77.
- Bangalore, M., Smith, A., Veldkamp, T., 2016. Exposure to floods, climate change, and poverty in Vietnam. World Bank, Forthcoming in the Policy Research Working Paper Series.
- Barbier, E.B., 2010. Poverty, development, and environment. *Environ. Dev. Econ.* 15, 635–660.
- Barbier, E.B., 2012. Natural capital, ecological scarcity and rural poverty. World Bank, Policy Res. Work. Pap. 6232.
- Barrett, C.B., Travis, A.J., Dasgupta, P., 2011. On biodiversity conservation and poverty traps. *Proc. Natl. Acad. Sci.* 108, 13907–13912.
- Brauer, M., Freedman, G., Frostad, J., van Donkelaar, A., Martin, R.V., Dentener, F., Dingenen, R. van, Estep, K., Amini, H., Apte, J.S., 2015. Ambient air pollution exposure estimation for the Global Burden of Disease 2013. *Environ. Sci. Technol.* 50, 79–88.
- Bui, A.T., Dungey, M., Nguyen, C.V., Pham, T.P., 2014. The impact of natural disasters on household income, expenditure, poverty and inequality: evidence from Vietnam. *Appl. Econ.* 46, 1751–1766.
- Carter, M.R., Little, P.D., Mogues, T., Negatu, W., 2007. Poverty Traps and Natural Disasters in Ethiopia and Honduras. *World Dev.* 35, 835–856.
- Dasgupta, S., Deichmann, U., Meisner, C., Wheeler, D., 2005. Where is the Poverty–Environment Nexus? Evidence from Cambodia, Lao PDR, and Vietnam. *World Dev.* 33, 617–638.
- Forouzanfar, M.H., Alexander, L., Anderson, H.R., Bachman, V.F., Biryukov, S., Brauer, M., Burnett, R., Casey, D., Coates, M.M., Cohen, A., 2015. Global, regional, and national comparative risk assessment of 79 behavioural, environmental and occupational, and metabolic risks or clusters of risks in 188 countries, 1990–2013: a systematic analysis for the Global Burden of Disease Study 2013. *The Lancet* 386, 2287–2323.
- Geographic Information Science and Technology, 2015. Landscan Population Data. Oak Ridge National Laboratory.
- Hallegatte, S., Bangalore, M., Bonzanigo, L., Fay, M., Kane, T., Narloch, U., Rozenberg, J., Treguer, D., Vogt-Schilb, A., 2016. Shock Waves: Managing the Impacts of Climate Change on Poverty, Climate Change and Development Series. World Bank, Washington, DC.
- Hansen, M.C., Potapov, P.V., Moore, R., Hancher, M., Turubanova, S.A., Tyukavina, A., Thau, D., Stehman, S.V., Goetz, S.J., Loveland, T.R., Kommareddy, A., Egorov, A., Chini, L., Justice, C.O., Townshend, J.R.G., 2013. High-Resolution Global Maps of 21st-Century Forest Cover Change. *Science* 342, 850–853.
- Harris, I., Jones, P. d., Osborn, T. j., Lister, D. h., 2014. Updated high-resolution grids of monthly climatic observations – the CRU TS3.10 Dataset. *Int. J. Climatol.* 34, 623–642.
- Kozel, V., 2014. Well begun but not yet done: Progress and emerging challenges for poverty reduction in Vietnam. World Bank Publications.
- Lanjouw, P., Marra, M., Nguyen, C., 2013. Vietnam’s Evolving Poverty Map: Patterns and Implications for Policy, Policy Research Working Papers. The World Bank.
- Narloch, U., 2016. The varying income effects of weather variation: Some insights from rural Vietnam. World Bank, Forthcoming in the Policy Research Working Paper Series.
- Petley, D., 2012. Global patterns of loss of life from landslides. *Geology* 40, 927–930.
- Petley, D.N., 2010. On the impact of climate change and population growth on the occurrence of fatal landslides in South, East and SE Asia. *Q. J. Eng. Geol. Hydrogeol.* 43, 487–496.

- Pham, T.T., Moeliono, M., Nguyen, T.H., Nguyen, H.T., Vu, T.H., 2012. The context of REDD+ in Vietnam: drivers, agents and institutions. Center for International Forestry Research (CIFOR), Bogor, Indonesia.
- Reardon, T., Vosti, S.A., 1995. Links between rural poverty and the environment in developing countries: asset categories and investment poverty. *World Dev.* 23, 1495–1506.
- Sidle, R.C., Ziegler, A.D., Negishi, J.N., Nik, A.R., Siew, R., Turkelboom, F., 2006. Erosion processes in steep terrain—truths, myths, and uncertainties related to forest management in Southeast Asia. *For. Ecol. Manag.* 224, 199–225.
- Sodhi, N.S., Koh, L.P., Clements, R., Wanger, T.C., Hill, J.K., Hamer, K.C., Clough, Y., Tscharntke, T., Posa, M.R.C., Lee, T.M., 2010. Conserving Southeast Asian forest biodiversity in human-modified landscapes. *Biol. Conserv.* 143, 2375–2384.
- Thomas, T., Christiaensen, L., Do, Q.-T., Trung, L.D., 2010. Natural disasters and household welfare: evidence from Vietnam. World Bank, Policy Res. Work. Pap. 5491.
- Vezina, K., Bonn, F., Van, C.P., 2006. Agricultural land-use patterns and soil erosion vulnerability of watershed units in Vietnam's northern highlands. *Landsc. Ecol.* 21, 1311–1325.
- Von Braun, J., Gerber, N., Mirzabaev, A., Nkonya, E., 2013. The economics of land degradation. ZEF Work. Pap. No 109.
- Vu, Q.M., Le, Q.B., Frossard, E., Vlek, P.L., 2014a. Socio-economic and biophysical determinants of land degradation in Vietnam: An integrated causal analysis at the national level. *Land Use Policy* 36, 605–617.
- Vu, Q.M., Le, Q.B., Vlek, P.L., 2014b. Hotspots of human-induced biomass productivity decline and their social-ecological types toward supporting national policy and local studies on combating land degradation. *Glob. Planet. Change* 121, 64–77.
- Winsemius, H., Jongman, B., Veldkamp, T., Hallegatte, S., Bangalore, M., Ward, P.J., 2015. Disaster risk, climate change, and poverty: assessing the global exposure of poor people to floods and droughts. World Bank, Policy Research Working Paper No. 7480.
- World Bank Group, 2016. Vietnam Systematic Country Diagnostics: Priorities for Poverty Reduction, Shared Prosperity and Sustainability. World Bank Group, Washington, DC.
- Wunder, S., Börner, J., Shively, G., Wyman, M., 2014. Safety Nets, Gap Filling and Forests: A Global-Comparative Perspective. *World Dev., Forests, Livelihoods, and Conservation* 64, Supplement 1, S29–S42.

Appendix

Table A.1 *Summary statistics of consumption, environmental risks and control variables, 2010, 2012, 2014*

Variable	Description	Type	Pooled Cross-Section			Panel Dataset	
			2010	2012	2014	2010-2012	2012-2014
Number of households			9,398	9,399	9,399	4,134	3,963
Consumption	Total per capita expenditure in 2011 PPP	Household - Time variant	2,965	3,188	3,395	258	236
<u>Environmental risks</u>							
Air pollution	Area-weighted mean PM2.5 concentration 2000-10 in micrograms per m3	Commune - Fixed	17.0	17.1	17.0	17.3	17.3
Tree cover loss	Share of forest area affected by tree cover loss in 2001-10	Commune - Fixed	1.5	1.5	1.5	1.6	1.5
Land degradation	Share of land area affected by significant biomass decline	Commune - Fixed	17.9	17.8	17.9	17.2	17.7
Slope	Area weighted average of slope categories: 1=least steep - 8=most steep	Commune - Fixed	3.37	3.38	3.37	3.41	3.39
Rainfall variability	Standard deviation of monthly rainfall 1981-2010	Commune - Fixed	55.2	54.6	55.8	54.9	56.4
Temperature variability	Standard deviation of mean annual temperature 1981-2010	Commune - Fixed	0.72	0.74	0.74	0.74	0.74
Flood hazard	Share of area at risk of a flood event with a 25 year return period	Commune - Fixed	32.1	32.0	32.0	31.8	31.8
Drought hazard	Number of months to overcome the maximum accumulated deficit volume	Commune - Fixed	1.03	1.03	1.03	1.04	1.03
<u>Control variables</u>							
Current rainfall	Average of monthly rainfall in survey year in mm	Commune- Time variant	142	183	169	41.3	-14.0
Current temperature	Annual average of monthly mean temperature in survey year in C	Commune- Time variant	26.0	25.5	25.2	-0.58	-0.13
Long-term rainfall	Mean of monthly rainfall in last 30 years	Commune - Fixed	157	156	158	156	158
Long-term temperature	Mean of monthly temperature mean in last 30 years	Commune - Fixed	25.4	25.4	25.5	25.4	25.4
Distance city	Distance from commune to next main city	Commune - Fixed	29.9	29.9	29.9	30.2	30.0
Distance road	Distance from commune to next road	Commune - Fixed	3.04	3.04	3.03	3.07	3.07
Area agriculture	Area for agricultural activities household has access to	Household - Time variant	3.86	3.99	3.93	0.18	0.09
Area forest	Forest area household has access to	Household - Time variant	1.83	1.47	1.34	0.36	-0.08
Area water surface	Water surface area household has access to	Household - Time variant	0.38	0.34	0.35	-0.02	0.02
Workforce	Share of household members involved in income generating activities	Household - Time variant	0.79	0.78	0.79	0.00	0.01
Education	Average number of school years of household members	Household - Time variant	6.48	6.56	6.66	0.12	0.02
Age head	Age of household head in years	Household - Fixed	48.3	49.7	50.7	50.4	51.3
Female head	Dummy = 1 if household head is female	Household - Fixed	0.25	0.25	0.26	0.25	0.25
Minority	Dummy = 1 if household belongs to ethnic minority	Household - Fixed	0.17	0.17	0.17	0.18	0.17

Notes: Table indicates mean values for each year for the Pooled Cross-Section. For the Panel Dataset, mean differences between years are presented for time variant variables and mean values for fixed variables.

Source: Authors' calculation based on data from Brauer et al., 2015, Hansen et al., 2013, Vu et al., 2014, Harmonized World Soil Database, Climate Research Unit, Bangalore et al., 2016, Winsemius et al., 2015, Lanjouw et al., 2013.

Table A.2 *Environmental risks across socio-economic groups, 2010, 2012, 2014*

	Air pollution	Tree cover loss	Land degradation	Slope	Rainfall variability	Temperature variability	Flood hazards	Drought hazards
<u>2014</u>								
Ethnic Minority	20.1***	3.12***	19.5**	5.81***	53.43***	0.84***	12.11***	1.11***
Poor	19.17***	3.15***	16.50	5.27***	58***	0.82***	17.08***	1.06**
Bottom 40%	18.02***	1.98***	17.35	3.89***	57.36***	0.77***	30.16***	1.07***
Top 60%	16.34***	1.2***	18.28	3.01***	54.82***	0.72***	33.33***	1.01***
Female-headed	16***	1.18***	19.07**	3.07***	54.59**	0.72***	31.90	1.02**
<u>2012</u>								
Ethnic Minority	20.43***	3.23***	19.31*	5.82***	53.07***	0.84***	12.03***	1.09***
Poor	18.37***	2.95***	18.36	4.94***	55.7*	0.79***	20.63***	1.09***
Bottom 40%	17.22	1.96***	18.44	3.87***	55.27**	0.75***	30.08***	1.08***
Top 60%	16.95	1.23***	17.47	3.06***	54.11**	0.73***	33.28***	1***
Female-headed	16***	1.22***	18.71	3.01***	53.26***	0.72***	33.32**	1.02
<u>2010</u>								
Ethnic Minority	20.27***	3.18***	20.05***	5.79***	52.98***	0.81***	12.14***	1.1***
Poor	18.4***	2.47***	19.04	4.67***	56.42**	0.77***	24.07***	1.09***
Bottom 40%	17.77***	2.06***	18.50	3.94***	56.69***	0.74***	30.04***	1.07***
Top 60%	16.58***	1.17***	17.48	3***	54.19***	0.71***	33.36***	1.01***
Female-headed	15.79***	1.25***	19.56**	3.05***	53.22***	0.7***	32.37	1.02**

Notes: Table indicates the mean value for the group, * 0.10 ** 0.05 *** 0.01 significance level from two-sample t-test for difference between group and non-group households.

Source: Authors' calculation based on data from Brauer et al., 2015, Hansen et al., 2013, Vu et al., 2014, Harmonized World Soil Database, Climate Research Unit, Bangalore et al., 2016, Winsemius et al., 2015, Lanjouw et al., 2013.

Figure A.1 *Overlay of poverty headcount and environmental risk categories at district-level*

Notes: Figures the district-level overlay of poverty and environmental risks maps based on the following categories (calculated as three terciles, with equal number of districts in each category): Poverty - Low = <15,000, Medium = 15,000-29,000, High = >29,000 based on number of poor people; Air pollution – Low = < 9.11 , Medium = 9.11-23.75 High = >23.75 based on area-weighted PM2.5 pollution levels (micrograms per cubic meter); Tree cover loss - < 0.21 , Medium = 0.21-2.28 High = >2.28 based on share of forest area affected by tree cover loss; Land degradation – Low = 0, Medium = 0.01-20.14 High = >20.14 based on area share affected by biomass loss; Slope - Low = < 2.7, Medium = 2.7-5.3 High = >5.3 based on area-weighted average of slope category; Rainfall variability - < 45.50, Medium = 45.50-61.44 High = >61.44 based on the long-term standard deviation of monthly rainfall; Temperature variability – < 0.61, Medium = 0.61-0.85 High = >0.85 based on based on the long-term standard deviation of monthly mean temperature; Flood hazards: Low = <10%, Medium = 10-30%, High = 30%> based on the area shared at risk of a 25-year return period flood; Drought hazards: - < 0.87, Medium = 0.87-1.04 High = >1.04 based on number of months to overcome water deficit during dry months.

Source: Authors' calculation based on data from Brauer et al., 2015, Hansen et al., 2013, Vu et al., 2014, Harmonized World Soil Database, Climate Research Unit, Bangalore et al., 2016, Winsemius et al., 2015, Lanjouw et al., 2013 and Geographic Information Science and Technology, 2015.

Figure A.2 *Environmental risks profiles across socio-economic groups in 2010 and 2012*

Notes: Spider diagrams show the mean risk values of households in each socio-economic group: household that belong to ethnic minorities (Minority), households below the national poverty line (Poor), the households in the lower two consumption quintiles (Bottom40), households in the upper three consumption quintiles (Top60) and households headed by women (Female-headed). Environmental risk values are standardized by subtracting their mean and dividing by the standard deviation. Descriptive statistics of all environmental risks variables with original units are shown in Table A.1.

Source: Authors' calculation based on data from Brauer et al., 2015, Hansen et al., 2013, Vu et al., 2014, Harmonized World Soil Database, Climate Research Unit, Bangalore et al., 2016, Winsemius et al., 2015, and VHLSS 2010 and 2012.

Figure A.3 *Environmental risks across consumption percentiles in rural and urban zones, 2012*

Notes: Binned scatterplots show the non-parametric relationship between consumption and environmental risks. X-axis shows percentiles of natural logarithm of per-capita expenditure in 2012. Y-axis indicates level of environmental risks.

Source: Authors' calculation based on data from Brauer et al, 2015, Hansen et al., 2013, Vu et al., 2014b, Harmonized World Soil Database, Climate Research Unit, Bangalore et al., 2016, Winsemius et al., 2015, and VHLSS 2012.

Figure A.3 *Environmental risks across consumption percentiles in rural and urban zones, 2010*

Notes: Binned scatterplots show the non-parametric relationship between consumption and environmental risks. X-axis shows percentiles of natural logarithm of per-capita expenditure in 2010. Y-axis indicates level of environmental risks.

Source: Authors' calculation based on data from Brauer et al., 2015, Hansen et al., 2013, Vu et al., 2014b, Harmonized World Soil Database, Climate Research Unit, Bangalore et al., 2016, Winsemius et al., 2015, and VHLSS 2012.