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Shock Waves: Managing the Impacts of Climate Change on Poverty

Background Paper

Environmental Reliance, Climate Exposure, and Vulnerability

A Cross-Section Analysis of Structural and Stochastic Poverty

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Abstract

This paper analyzes environmental reliance, poverty, and climate vulnerability among more than 7,300 households in forest adjacent communities in 24 developing countries. The data are from the detailed, quarterly income recording done by the Poverty Environment Network project. Observed income is combined with predicted income (based on households' assets and other characteristics) to create four categories of households: income and asset poor (structurally poor), income rich and asset poor (stochastically non-poor), income poor and asset rich (stochastically poor), and income and asset rich (structurally non-poor). The income and asset poor generate 29 percent of their income from environmental resources, more than the other three categories. The income poor are more *exposed* to extreme and variable climate conditions. They tend to live in dryer (and hotter) villages in the dry forest zones, in wetter villages in the wet zones, and experience larger rainfall fluctuations. Among the self-reported income-generating responses to income shocks, extracting more environmental resources ranks second to seeking wage labor. Given high reliance on forest and other environmental resources, a concerning finding is that, in the Africa subsample (dominated by dry forests), the rate of forest loss is more than four times higher for the income & asset poor compared with the income & asset rich. Special attention should be given to the poorest households in dry areas, predominantly in Africa. They are (already) exposed to more extreme climate conditions, they suffer the highest forest loss, and the forest benefits are at risk in global warming scenarios.

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Environmental Reliance, Climate Exposure, and Vulnerability: A Cross-Section Analysis of Structural and Stochastic Poverty

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1 Introduction[1]

This paper addresses the interaction between climate and weather variability and shocks, exposure and vulnerability, poverty and environmental reliance. We seek to answer two broad questions. First, are the poor more exposed to climate extremes, weather anomalies and other shocks? Second, what is the role of environmental income in coping with shocks, and how does the role vary across poverty groups? Answers to these questions will help policy makers better understand how climate change might affect the poorest, and whether and how their access to natural resources – and sustaining the resource base – might help them cope with climate shocks.

We address these questions by using a global sample of nearly 8,000 rural households in 59 sites in 24 developing countries from the Poverty Environment Network (PEN) project.[2] We define environmental income as cash and subsistence incomes from products extracted from non-cultivated (wild) areas. Environmental income accounts for 27% of total household income, suggesting that it plays an important role in income portfolios of rural households in developing countries, and needs to be factored into discussions on climate change and vulnerability. We argue that environmental income has characteristics, in terms of being more climate-resilient and relatively more accessible to the poor, which can increase the adaptive and coping capacity of poor households. At the same time, this key source of rural livelihoods is under threat by the degradation of natural resources in many parts of the developing world.

Climate change has both direct and indirect impacts on the livelihoods of the rural population in developing countries (Porter et al. 2014). Climate change is likely to have a negative impact on long term crop yields, affecting agricultural income directly. The impact will vary, however, depending on the nature of climate change (e.g. some areas may experience more and others less rainfall) as well as the differences in initial conditions (e.g. wet vs. dry areas). Climate change is also likely to impact the provision of environmental resources, such as the availability of and access to forest products. Changes in crop prices, wages, seasonal wage employment opportunities in agriculture, and alternative livelihood opportunities are potential indirect impacts of climate change. The large uncertainties of the magnitude and impacts of climate change underscore the importance of strengthening the adaptive and coping capacities of the poor.

While our data do not allow us to look at exposure and vulnerability to future climate changes *per se*, studying current impacts of climate variability, weather anomalies and the self-reported shocks can shed light on possible climate impacts in the future. Moreover, *current* climate-related shocks already pose a challenge for poor people, thus also current exposure and vulnerability deserve the attention of policy makers.

A major contribution of the paper is to distinguish clearly between categories of poor. We differentiate between stochastic (temporary or transient) and structural (permanent, persistent or chronic) poverty. While the observed income in the survey year is of interest, it does not necessarily capture the likely income next year, nor the chances that a household will fall into (deeper) poverty in the event of a shock (vulnerability). We use the method outlined in Dokken and Angelsen (2015), and argue that *predicted* income, based on a range of assets and other household and context

[1] An accompanying paper by Noack et al. (2015) describes households' environmental use in the PEN data set, and provides an econometric analysis of how climate shocks – through loss of crop income – might impact extraction of environmental resources. The two papers are complementary, and we refer at times to the Noack et al. paper for further elaborations.

[2] See Angelsen et al. (2014) for details on the PEN project.

characteristics, is a better measure of long-term income than the observed one-year income. Predicted income should complement the conventional approach of defining poverty groups.

Using median observed and predicted incomes as the cut-off levels, we identify four different categories of households: (i) *income & asset poor* (low observed and low predicted income, the structurally poor), (ii) *income rich & asset poor* (high observed and low predicted income, the stochastically non-poor), (iii) *income poor & asset rich* (low observed and high predicted income, the stochastically poor), and (iv) *income & asset rich* (high observed and high predicted income, the structurally non-poor). The background for this classification is given in section 2.

We also we present key climate concepts and the terminology of the fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC AR5) report (Field et al. 2014), which distinguishes between *exposure* and *vulnerability*, with the latter including adaptive and coping capacities. We provide a brief discussion of likely implications of climate change on natural resource systems and on livelihoods.

The data and methods are described in section 3. The poverty classification and the main analysis are done using the global data set of the PEN project. Climate data are from the Climate Research Unit (CRU) of the University of East Anglia, while forest cover data are MODIS-based (Hansen et al. 2010). The results for the income prediction and the subsequent household categorization is presented.

Section 4 addresses three specific questions related to *exposure*: (i) Are the poor more exposed to extreme climate conditions (temperature and rainfall), including higher climate variability? (ii) Is exposure to large weather anomalies in the survey year related to lower household income, and how does exposure to anomalies vary across poverty categories? (iii) Are self-reported shocks related to lower household income, and how does shock exposure vary across poverty categories?

Section 5 addresses three specific questions related to *vulnerability* and environmental income: (i) Do the income and/or asset poor households have higher environmental reliance and higher income diversity? (ii) How important is increased harvesting of forest and other wild products as a coping strategy after a shock, and how does this strategy vary across households, and type and severity of the shock? (iii) Do the income and/or asset poor have poorer physical access to forest resources and are their resource base more exposed to degradation? We conclude and provide some policy recommendations in section 6.

2 Concepts and frameworks

2.1 Climate terms

"The climate is what you expect; the weather is what you get" (unknown).

Climate change refers to "a statistically significant variation in either the mean state of the climate or in its variability, persisting for an extended period" (IPCC 2001, Glossary). *Climate variability* is a related concept, and refers to "variations in the mean state and other statistics (such as standard deviations, the occurrence of extremes, etc.) of the climate on all temporal and spatial scales beyond that of individual weather events" (IPCC 2001, Glossary).

We look at the mean and standard deviation of rainfall and temperature over a 30 year period in the study sites, and refer to these as *climate conditions*. We do not assess whether these have changed systematically over the 30 year period (climate change). While climate change refers to long-

term change in these parameters, *weather* is used for the realized state of the parameters. We use the term *weather anomalies* to refer to deviations from the mean (over the 30 year period) in rainfall and temperature during the one year period for which household and village data were collected.

To assess the impact of climate change on rural livelihoods, we follow the disaster risk management typology of IPCC AR5 and its three key elements: *weather and climate events, exposure and vulnerability* (i.e. vulnerability does *not* include exposure) (Field et al. 2014). Vulnerability then refers to "the propensity or predisposition to be adversely affected", while also adding that it "encompasses a variety of concepts and elements including sensitivity or susceptibility to harm and lack of capacity to cope and adapt" (Agard et al. 2014).[3] When discussing households' *adaptive and coping capacity* (section 5), we follow mainstream literature, and refer to adaptation as *ex ante* strategies and coping as *ex post* strategies.[4]

2.2 Impacts of climate change

Climate conditions and change in these (climate change) affect rural livelihoods and vulnerability though multiple channels, as elaborated by Hallegatte et al. (2014), making the final net impact hard to measure. The uncertainties are large with respect to both the degree and nature of climate change, the impacts on natural systems, and the impact on humans. The high uncertainty in itself underscores the importance of a focus on the adaptive and coping capacities of the poor.

The primary economic sectors, including agriculture and forestry, are more sensitive to future climate change because of their direct dependence on the natural environment (Arent et al. 2014). According to IPCC AR5, the impacts of climate change on crop production is evident in several regions, with negative impacts outweighing the positive ones (Porter et al. 2014). The future scenarios vary greatly by crops and regions and have high levels of uncertainty.

A review of Global Gridded Crop Models (GGCMs) points to a likely decrease in the yield of key crops in low-latitude (tropical) areas. "In low-latitude regions, even moderate temperature increases (1 to 2 °C) were found to have negative yield impacts for major cereals, because the climate of many tropical agricultural regions is already quite close to the high-temperature thresholds for suitable production of these cereals" (Rosenzweig et al. 2014: 3269). Warming has, however, benefitted crop yields in high altitude regions, including China (Porter et al. 2014).

Most model scenarios concentrate on climate means. "By concentrating on changes in climate means, the full impacts of climate change on biological and human systems are probably being seriously underestimated" (Thornton et al. 2014, 3313). The IPCC AR5 concludes that "climate change will increase crop yield variability in many regions" (Porter et al. 2014, 505). Additional uncertainties relate to pests, water scarcity, tropospheric O_3, and soil degradation.

Almost all the crop systems in the PEN sites are rainfed, making them sensitive to changes in rainfall (mean and seasonal pattern). Future precipitation change is highly uncertain and varies considerably between climate models (Scholes et al. 2014). There is some agreement that, for example, the Amazon basin will experience lower rainfall and more frequent droughts (as already has been observed). For Africa, some climate models predict that the southern and northern (Sahel)

[3] The term "vulnerability" is used broadly in the literature, and represents a "conceptual cluster" for human-environment research, with competing terminologies that is challenging when undertaking and interpreting research (Füssel and Klein 2006).

[4] Dercon (2002, 145) argues, however, that the distinction is less relevant as coping strategies also require *ex ante* actions to prepare for the shock. Yet, in the literature coping is now commonly referring to responses after the shock has occurred, i.e., the *ex ante* strategies (e.g., Heltberg et al. 2015), while adaptation is at times used to encompass both, but with an emphasis on the *ex post* strategies.

regions are likely to receive less and the central and eastern regions more precipitation during the 21st century (Niang et al. 2014).

The paper focuses on income derived from natural environments, which are likely to be exposed to higher stress. A key uncertainty concerns the strength of direct CO_2 effects on photosynthesis and transpiration (Scholes et al. 2014, 307). In general, "tropical species, which experienced low inter-and intra-annual climate variability, have evolved within narrow thermal limits, and are already near their upper thermal limits" (page 301). The IPCC AR5 further notes that "to our knowledge nothing has been published for hunting or collection of wild foods other than capture fisheries" (Porter et al. 2014, 494).

It can be argued that for the short term, production based on harvesting of *stocks* of biomass, such as timber and fuelwood, are less sensitive to changes in climate parameters compared to production which is based on annual increments (*flows*) in resource based systems such as harvesting of wild food and crop production (e.g., Nøstbakken and Conrad 2007).[5] About 60% of the forest income among the households in our sample are woodfuel (fuelwood and charcoal) or structural and fiber products (Angelsen et al. 2014).

In addition to the direct production (yield) effects of climate change, prices are also likely to change through general equilibrium effects. Rural households that are net food buyers will lose from higher food prices. However, there are various channels through which rural households could benefit, and these can partly offset or even outweigh the income losses from declining yields and the expenditure increase from higher agricultural commodity prices. Net-producers should benefit through higher profits, agricultural laborers could benefit from increasing rural wages, and farmers can make long-term adjustments in production to benefit from higher prices.

In terms of implications for livelihood and poverty, the IPCC AR5 concludes that "climate change will exacerbate multidimensional poverty in most developing countries" (Olsson et al. 2014, 797). While some of the overall trends, such as higher yields for some crops in some areas, might be positive, higher climate variability will increase the frequency and severity of shocks that poor households face. Households may be able to cope with a shock during one year, for example, by selling liquid assets, but multi-year shocks will deplete their buffers. The livelihood impact also depend on their capacity to adapt, e.g., by modifying the cropping seasons or planting crops or crop varieties more suitable to the changed rainfall and temperature patterns.

2.3 Income fluctuations and poverty categories

The activities rural households in developing countries engage in depends on the assets they possess and the relative returns to these assets. The returns to and availability of assets vary from year to year, causing total household income to fluctuate over time. Crop yield responds to weather conditions, and market prices change from year to year. Some households are exposed to idiosyncratic (household specific) shocks such as illness, or covariate (common) shocks such as yield-reducing drought or an economic recession that reduce wage income. In a study from Ethiopia, Dercon and Krishnan (2000) found that one third of the households identified as poor in the first year in a two-year panel data set were different from the households identified as poor the second year.

While *poverty dynamics* is widely recognized and has become a key concept in the poverty literature (e.g., Baulch and Hoddinott 2000), cross-sectional studies of poverty-environment

[5] See also discussion of this point in Noack et al. (2015).

relations typically do not take into account that incomes fluctuate greatly from year to year. A one-year income measure gives a snapshot and static picture of the households' economic status, and fails to take into account the dynamics of poverty (e.g., Hulme and Shepherd 2003). This has made some propose to take asset holdings into account when assessing a household's poverty status. Carter and May (2001), among others, highlight the importance of assets in poverty analysis, and distinguish between structural (permanent or chronic) and stochastic (temporary or transient) poverty.

In the current paper we extend this approach. Using the method outlined in Dokken and Angelsen (2015), we predict household income based on a range of assets and other household and context characteristics to distinguish between structural and stochastic poverty. We categorize households into the four different categories, based on their observed and predicted income being below/above the poverty line, in a way that resembles the categorization done with panel data.[6] Our approach has several advantages compared to a more conventional approach of using the overall value of assets or an asset index. We can include a broader range of variables that are important in determining household income. Also, we avoid the problem of converting all assets into a monetary value. The regression analysis provides an estimate of the marginal returns to various assets and characteristics.

Households are then classified to belong to one of four categories, as shown in Table 1: We refer to these as the: (*i) income & asset poor, (ii) income rich & asset poor, (iii) income poor & asset rich,* and *(iv) income & asset rich*. We use the term "asset poor" in the meaning of "low predicted income"; while assets are critical to predict income, a key point above is that we include other characteristics in an "augmented asset approach" in the regressions to predict income.

Table 1: Household poverty categories, based on low (< median) and high (> median) observed and predicted income

		Predicted income (incl. assets)	
		Low	**High**
Observed income	**Low**	Income & asset poor (structurally poor)	Income poor & asset rich (stochastically poor)
	High	Income rich & asset poor (stochastically non-poor)	Income & asset rich (structurally non-poor)

Our distinction between stochastic and structural poverty is relevant for the vulnerability discussion. In their study of long term asset accumulation and income poverty in Ecuador, Moser and Felton (2007) find that stochastically non-poor (*income rich & asset poor*) are very vulnerable. Relatedly, Dercon (2002) propose that "vulnerable households" could be defined as those that will fall below a pre-set poverty line with a certain probability. From a vulnerability perspective, one might therefore argue that *predicted* income based on a range of assets and other household and context characteristics is a more useful variable than observed one-year income. Predicted income should complement the conventional approach (when using cross-sectional data) of simply splitting the sample into poor and non-poor based on observed income. The definition of poverty groups matters for policy makers because it can improve the targeting of households and identify

[6] Our approach extends the work by Nielsen et al. (2012). They use both income and households' liquid asset holdings to define poverty groups. We include a wider range of household assets and characteristics to predict income.

structurally vulnerable households. Households with low asset holdings have, in general fewer means to cope with shocks, e.g. few liquid assets to sell to cope with an income loss.

Finally, a diversified income portfolio can be viewed as a deliberate risk management (adaptation) strategy that aims to reduce vulnerability (e.g., Fafchamps 2003).

2.4 The role of environmental income in rural livelihoods

Understanding the importance of natural resources and the contribution of environmental income in rural livelihoods and economies is important to understand the welfare implications of climate change – including the coping strategies available, and also to design effective development and conservation strategies that are adapted to future climate change scenarios. For a comprehensive analysis and discussion of environmental income in rural livelihoods, using the same PEN data set as in this paper, we refer to the special issue of World Development (Wunder et al. 2014a), with articles on the overall contribution and distribution of environmental incomes (Angelsen et al. 2014), the role as a safety net and seasonal gap-filler (Wunder et al. 2014b), the role of tenure in shaping forest income (Jagger et al. 2014), the gender division of environmental income (Sunderland et al. 2014), and forest conversion and poverty (Babigumira et al. 2014). The accompanying working paper by Noack et al. (2015) also provides summary data.

The literature distinguishes between three potential functions of environmental income in rural livelihoods (Angelsen and Wunder 2003, Cavendish 2002). Environmental income can: (i) support current consumption and subsistence needs, (ii) serve as a safety net, or (iii) provide a pathway out of poverty. Many studies focus on forest income rather than the broader environmental income (i.e., including incomes from non-forest, natural habitats). These find that forest income mainly supports current consumption, such as the study by Kamanga et al. (2009) from Malawi, Nielsen et al. (2012) in the Democratic Republic of Congo, Heubach et al. (2011) in Benin and by Rayamajhi et al. (2012) in Nepal. The importance of this role is also supported in the PEN data (Angelsen et al. 2014).

Several studies also recognize that forest income may serve as a safety net in case of a negative income shock, one of the questions raised in this paper. Debela et al. (2012) provides an example from Western Uganda, where large negative shocks were associated with a higher use of forest resources in subsequent periods, particularly among the asset poor households. The work based on the PEN data by Wunder et al. (2014b) provides a nuanced view of the universality of this pattern.

Finally, and also relevant for our paper, some studies suggest that commercially valuable forest products, when they exist, might lift (asset) poor people out of poverty (Ruiz-Pérez et al. 2004, Ainembabazi et al. 2013, Duchelle et al. 2014). There are, however, many hurdles to such a scenario, as elaborated in Angelsen and Wunder (2003): high value products might be captured by the elite (the Dove hypothesis); the resources can become privatized, which also tends to exclude the poorest; high rents can lead to overexploitation and a "tragedy of the commons" (the Hardin hypothesis); or the products are domesticated, lowering the prices of wild products (the Homma hypothesis).

3 Data, methods and poverty classification

3.1 The PEN data set[7]

PEN is a large collaborative research project, coordinated by the Center for International Forestry Research (CIFOR).[8] PEN was a network of primarily PhD students, doing fieldwork and data collection in a predetermined format and standardized questionnaire. PEN represents the largest quantitative, global-comparative research project on forests and rural livelihoods to date. The surveys covered a 12 month period, with village surveys and household surveys at the beginning and the end of the survey period collecting basic household-level variables (demographics, assets, income sources, social capital), and village-level data (demographics, markets, institutions, natural resource endowments) (see Figure 1). The core of the data collection was, however, four quarterly household income surveys, covering all household incomes using one or three months recall periods, depending on the regularity of the income source. The data collection was done in 2005-2009, with close to 70% of the surveys conducted in 2006 and 2007.

The case study selection by the PEN partners was to some degree opportunistic. Study sites were to be selected within tropical or sub-tropical regions of Asia, Africa or Latin America, and in close proximity to forests. The sample is considered to be "representative of smallholder-dominated tropical and sub-tropical landscapes with moderate-to-good access to forest resources" (Angelsen et al. 2014: 3). Natural variation was ensured through a deliberate selection of villages within study sites to reflect variation in important characteristics (e.g., market access and tenure), and by random sampling of households within selected villages. Larger PEN study area with distinct geographical sub-areas were split into "sites", yielding a total of 59 sites, 334 villages and 7,978 households with complete income data. In the analysis of this paper, the sample is smaller (7,329), as some variables that we used to predict income were missing for some households.

The PEN guidelines emphasize that households' subsistence extraction and production (i.e., in addition to extraction/production that generates cash income) should be included in total income. Key sectoral incomes are defined as follows:

Agricultural income is split into *crop* and *livestock* income. Income is defined as the gross value (quantity produced multiplied by price) minus the costs of purchased inputs (e.g., fertilizers, seeds, tools, hired labor, marketing costs). Following the standard income definition, the value of family labor should not be deducted. Crop income comes from cropping on land categorized as agriculture, and agroforestry. Livestock income comes from products (including the sale of live animals) and services (e.g., rented-out horsepower), but excludes non-realized incremental changes in stock values, which are captured in the value of assets. Livestock also includes fish-farming (aquaculture).

Forest income is income from resources extracted in forest areas, using the FAO definition: "forests are lands of more than 0.5 hectares, with a tree canopy cover of more than 10%, where the trees should be able to reach a minimum height of 5 meters *in situ*, and which are not primarily under agricultural land use" (FAO 2000). This includes both primary and secondary forests, native and exotic species, natural and planted forests, as well as closed and open forests. In some analyses, a distinction is made between income from *natural forests* and from *plantations*. Forest income also includes direct payments for forest-based environmental services, e.g., carbon credits or profits from community-based forest ecotourism.

[7] This section draws heavily on Angelsen et al. (2014).
[8] For further information, see http://www1.cifor.org/pen

Environmental income is in the PEN guidelines defined as "incomes (cash or in kind) obtained from the harvesting of resources provided through natural processes not requiring intensive management". It includes income from natural forests (*forest environmental income*) and non-forest wildlands such as grass-, bush- and wetlands, fallows, but also wild plants and animals harvested from croplands (*non-forest environmental income*). Thus all forest income, except income from plantations, is defined as environmental income.

All incomes are transformed to US dollar (USD) purchasing power parity (PPP) rates of the survey year (2005-2009).[9] For inter-household comparisons of incomes and asset holdings we use adult equivalent units (AEU). A range of methods is available for calculating adult equivalents (Deaton 1997). We use the OECD adult equivalence scale: the first adult counts as 1 unit, the following adults (>15 years) ones count as 0.7, while children count as 0.5. For the regressions underlying the income predictions we separate between different household member groups. We differentiate between males and females, and children (<15), adults (15-65) and elders (>65).

The PEN survey also asked households if they had experienced any "major income shortfalls or unexpectedly large expenditures during the past 12 months", i.e., the period covered by the income survey. We categorized them *ex post* into the following categories: (i) *income shock*: serious crop failure, lost wage employment or delays in payments of products during the period covered by the income surveys; (ii) *labor shock*: serious illness or death of a productive age household member; and (iii) *asset shock*: loss of land, livestock or other major losses of assets. Households were also asked about the severity of the chock, distinguishing between moderate and severe ones.

3.2 Climate and forest cover data

To relate the household data to climatic conditions we use the gridded climate data of the Climate Research Unit of the University of East Anglia (CRU TS3.21). The CRU data contain monthly time series of temperature, precipitation and other climate variables spanning the period from 1901 to 2012 and covering the whole globe with 0.5x0.5 degree resolution. It is based on the analysis of over 4,000 individual weather station records (Harris et al. 2014).

A normal climate is defined as the mean precipitation (mm per year) and temperature (degrees Celsius) in the village during the period 1981-2010. Weather anomalies refer to deviations in precipitation and temperature during the survey period, defined as the year that starts two month before the first interview in the respective village. We use the term "weather anomaly" rather than "climate shock", as it refers to only one year. For further details about the CRU data, we refer to Noack et al. (2015).

In much of the analysis we distinguish between wet and dry villages (areas), using 1,500 mm of rain during the 1981-2010 period as a cut-off point. The impacts of more rain, for example, might be very different in the two areas. All PEN sites in Latin America are in wet areas, while most of the African sites are in dry areas. The exceptions in Africa are the wet sites in Cameroon and Nigeria. India and Nepal in South Asia have a mix of wet and dry sites, while China has the only dry site in East Asia.

Finally, we use data from Hansen et al. (2010) to provide estimate of tree canopy cover and change in tree canopy cover for the period 2000-2010. The data use annual MODIS-satellite based estimations of tree canopy cover at 250 m spatial resolution globally. The data used in this paper are

[9] We used the PENN World Tables, ver. 7.0 http://pwt.econ.upenn.edu/php_site/pwt_index.php.

mean tree cover for 2000-2010 as average of all estimates for 2000-2010, and tree canopy cover change 2000-2010 as the difference between the tree canopy cover average for 2009/10 and the average for 2000/01.[10]

3.3 Predicted income

3.3.1 Methods

Income is generated from activities the household undertake and this in turn depends on the return to assets the household control or have access to. Household assets include: (1) physical capital such as agricultural land and livestock; (2) human capital, both the number of workers and their education, skills and health; (3) financial capital, including savings, and; (4) social capital assets, such as network in the community (which may, for example, result in higher output prices). In addition, the household may have access to, without exclusive ownership: (5) natural capital, such as forests and other environmental resources; (6) public infrastructure such as roads and markets; and (7) political capital, determining rights and obligations through, for example, local institutions and the rule of law.

The return and access to the different assets are likely to vary from one year to another, depending on weather conditions for farming, access to markets and price fluctuations, health status and so on. Returns to assets also differ across households due to different production technologies and skills. We do not attempt to estimate a production function *per se*, but rather a revenue function to estimate how different assets are correlated with income. The regression coefficients may serve as a proxy for the returns to assets. We estimate the following equation:

$$lnY = \beta_0 + \beta_1 Physical + \beta_2 Human + \beta_3 Financial + \beta_4 Social + \beta_5 Natural + \beta_6 Infra + \beta_7 Political + u$$

where the dependent variable is log of total household income Y (in PPP adjusted USD). The variables included in the model are presented in the appendix (Table A1).

We expect coefficients to vary greatly across regions, and estimate separate models for each of the four regions; Latin America, South Asia, East Asia and Africa. We also expect standard errors to be correlated across individuals in the same village, and therefore cluster the standard errors at village level. We disregard increasing or decreasing returns to scale and interaction effects, although we do acknowledge that such interaction effects may exist (e.g., between land and education).

Based on the region specific correlation coefficients, we predict total household income based on the asset holdings of the household in the survey year, and use this as a proxy for the structural household income. This predicted income is used to classify households into our categories of: (i) *income & asset poor*, (ii) *income rich &asset poor*, (iii) *income poor &asset rich*, and (iv) *income &asset rich*.

There are two possible interpretation of this categorization. The main one – which forms the rationale for our approach – is that the predicted income represents the expected income in a normal year for the household, i.e., the structural income. The deviation from this, due to bad or good fortunes, can put the household temporarily in another category (stochastically poor/non-poor). Any income above the predicted income might be termed stochastic income. The predicted

[10] Since no village borders exists in digitalized format, for the purpose of tree cover estimation (share of total land area) we define a village as a circle around the village center with a radius of 5 km.

income should therefore reduce the effect of inter-annual income fluctuations, and provide a more appropriate picture of the household's poverty status.

An alternative interpretation of the discrepancy between predicted and observed income is the following: There might be elements that affect household income that we have not included in the regression model. First, there are relevant factors that we do not have data for (unobservables). For example, some of the *income poor &asset rich* may have characteristics that make them unable to use productively the assets they own, e.g., they have a chronic disease that makes them unable to use fully the agricultural land that they possess. Second, there are potentially relevant variables that we have some data for but that are not included, such as weather anomalies or access to environmental resources. For example, some of the asset poor household may have (under-predicted) high environmental income that brings them above the income poverty line (i.e. make them belong to the category of *income rich &asset poor*). Such hypotheses are addressed in the paper. For this reason, variables such as access to forest resources, weather anomalies and shocks are excluded from the regression of predicted income, as we test whether these can explain why a household falls in a particular poverty category. [11]

3.3.2 Classification into poverty categories

The combination of observed and predicted income is used to classify households into the four poverty categories. Summary statistics for the variables included in the regression models are presented in the Appendix (Table A2-A7). Agricultural land, livestock and financial assets are key predictors of household income, and these vary greatly across the regions. The mean total income among the households in Latin America is more than three times higher than mean income among the households in Africa, and the value of assets is more than five times higher. The households in Latin America also hold more livestock and have more agricultural land.

The regression model results that underlie our income predictions are given in the Appendix Table A8. Most results are in line with expectations. The range of predicted income is much smaller than for observed income, as would be expected (Table 2).[12] The difference in mean observed and mean predicted income is due to the smearing estimate.[13] Also, we note that the median observed income is well below the median predicted income. Income distributions typically has a long right tail, resulting in the mean being well above the median income (only about one third of the households have an income above the mean). The predicted incomes have a more normal distribution, with the mean and median being closer.

[11] Alternatively, we could have included indicators for shock, weather anomalies and access to environmental resources in the regressions of predicted income, which would then test to what extent these variables are relevant to predict income. The approach chosen, to test for systematic differences in, for example, exposure to shock and weather anomalies across the groups, gives, in our view, a more transparent and clearer analysis.

[12] Some of this difference in number of poor could also be explained by measurement errors, i.e., some households are classified as poor based on the observed income simply because of incomplete income recording. While we cannot exclude that this explains some (unknown) proportion of the difference, the PEN studies did – more than most household surveys – put much efforts into carefully recording all income sources in the four quarterly income surveys done over the one year study period.

[13] When transforming the income variable back from log to the level variable to estimate the predicted income, we adapt the smearing estimate developed by Duan (1983) to avoid the retransformation bias and underestimation of predicted income.

Table 2: Comparison mean and median observed and predicted yearly income (AEU USD PPP)

WB region	Income	Mean	Median	Std.dev	Min	Max	N
Latin America	Observed	4 850	3 014	6 491	225	76 535	848
	Predicted	4 751	3 542	4 234	372	48 844	848
South Asia	Observed	1 459	1 139	1 370	129	26 156	1 094
	Predicted	1 439	1 321	668	296	5 013	1 094
East Asia	Observed	1 675	1 239	1 922	0	39 619	1 297
	Predicted	1 678	1 535	908	215	6 371	1 297
Africa	Observed	1 015	526	2 585	13	100 351	4 090
	Predicted	940	683	858	63	15 731	4 090
Total	Observed	1 642	832	3 309	0	100 351	7 329
	Predicted	1 586	1 060	2 023	63	48 844	7 329

Based on the poverty categorization (Table 1) and the predicted income from the regression analysis, the distribution of households across poverty categories is presented in Table 3. Naturally, most households are in the *income & asset poor* or *income & asset rich* categories, with 39.1% in each. 10.9% are in each of the *income poor & asset rich* or *income & asset rich* categories, with the shares being slightly higher in South Asia (12.1%) and East Asia (13.4%).

Table 3: Number of households in different poverty categories across regions

Region	*Income & asset poor*	*Income rich & asset poor*	*Income poor & asset rich*	*Income & asset rich*	N
Latin America	345	79	79	345	848
South Asia	414	133	133	415	1094
East Asia	474	174	174	414	1297
Africa	1630	415	415	1630	4090
Total	2863	801	801	2864	7329

Notes: *Income & asset poor:* observed and predicted income below the median.
Income rich & asset poor: observed income above the median, predicted income below the median.
Income poor & asset rich: observed income below the median, predicted income above the median.
Income & asset rich: observed and predicted income above the median.

The groups are significantly different from each other with respect to assets (see Table A9), not surprising since asset holdings partly formed the basis to categorize households. But there are some interesting anomalies. While the *income & asset poor* and *income rich & asset poor* have less agricultural land per adult equivalent and less financial assets, they have *more* labor available within the household (a factor contributing to higher income). A notable exception from this pattern is livestock holdings. At the global level, the *income rich & asset poor* have almost twice as much livestock as the *income & asset poor*. Further, the household head of *income & asset poor* and *income rich & asset poor* are older on average and a larger share are female headed in our global sample.

3.4 Scope and limitations of study

The PEN data set, reviewed in section 3, constrains our analysis in some important ways. First, we do not have a large panel data set for different scales, which would be needed to fully assess climate change over time and different stressors, pathways of impact, and thresholds. Using cross-sectional data to discuss dynamic phenomena is not uncommon, but has its limitations as elaborated further in Noack et al. (2015). We study forest-adjacent communities with different

climatic conditions. These communities have, however, adapted to the conditions over a long period of time, while the predicted climate changes will be relatively more abrupt. In the paper we therefore refer to climate conditions or weather anomalies rather than climate change.

The PEN data set is mostly representative for smallholder-dominated tropical and sub-tropical rural landscapes with moderate-to-good access to forest resources, and all but very high population densities (Angelsen et al. 2014). The households are in the poorest segments of their countries. Further, in the year of data collection, none of the sites experienced major covariate shocks (Wunder et al. 2014). Our analysis, given the constraint of the dataset, can only provide a partial analysis of the complex relationship between poverty, environmental income, vulnerability and climate change.

4 Exposure to climate conditions, weather anomalies and self-reported shocks

4.1 Climate conditions

Our first research question is: *Are the poor more exposed to extreme climate conditions (temperature and rainfall), including higher climate variability?* We calculated the mean and variability (standard deviation) of rainfall and temperature for the period 1981-2010, based on data described in section 3.2. We focus first on observed income only, as we controlled for mean precipitation and temperature in the regression model for predicted income. We also note that causality could run both ways: extreme climate conditions can reduce income and assets, and create or deepen poverty, but the least resourceful (asset poor) might also locate themselves in harsher climate conditions, e.g., they cannot afford to buy land in more favorable climates.

The poor households tend to live in dryer and warmer villages in the dry area, and wetter and colder sites in the wet area (defined as rainfall above 1500 mm/year over the 30 year period) (Table 4). The differences in mean temperature and precipitation between the poor and non-poor are statistically significant (except for temperature in dry areas), although the magnitude of the differences is rather small: 5-7% for rainfall, and less for temperature (0.5 degree C for wet areas).

Table 4: Climate conditions over the period 1981-2010 in the study villages

		Poor (below median income)	Rich (above median income)	Difference t-value (two sided)
Dry area				
Precipitation (mm/yr)	Mean	1101	1160	14.55***
	Standard deviation	197	180	11.4***
Temperature (degree C)	Mean	23.0	22.8	1.08
	Standard deviation	0.39	0.42	8.19***
Wet area				
Precipitation (mm/yr)	Mean	2280	2127	7.80***
	Standard deviation	325	277	9.94***
Temperature (degree C)	Mean	24.1	24.6	3.24***
	Standard deviation	0.36	0.34	4.99***

*, **, *** Significantly different at 0.1, 0.05 and 0.01 level.

In terms of climate variability, as measured by the standard deviation (SD), the income poor tend to live in villages that experience larger precipitation variability. We observe this pattern in both

wet and dry areas. The differences are significant and pronounced. For example, the SD of rainfall that poor households in wet areas experience is 17% higher compared to the rich (above median) households. For temperature variability, the picture is mixed: in dry areas the poor have experienced less variability, while they have experienced more in the wet areas.

4.2 Weather anomalies

Our second research question is: *Is exposure to large weather anomalies in the survey year related to lower household income, and how does exposure to anomalies vary across poverty categories?* To address this, we first look at the relationship between income and rainfall in the survey year. Figure 1 presents a distinct bell-shaped relationship.[14] The relationship is robust, also after controlling for other factors, such as regions (see also discussion in Noack et al., 2015).

The poorest villages are found in driest areas, but these areas also have a huge variation in average household income. The peak income is at around 2,000 mm/year, after which mean income tends to decrease.

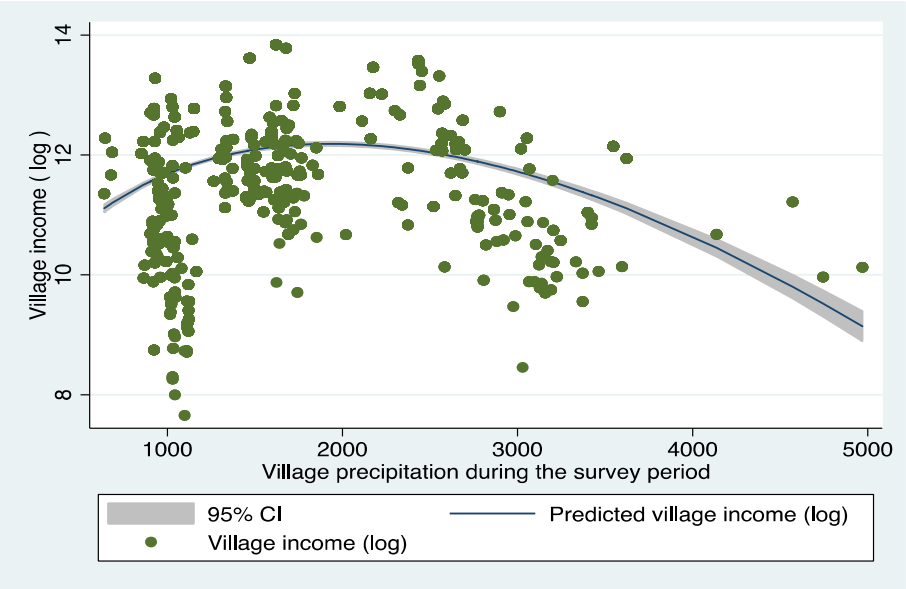

Figure 1: Relationship between rainfall and mean observed income, at village level

Next, we investigate whether exposure to weather anomalies (during the survey year) had a negative impact on household income. How is exposure to weather anomalies correlated with whether households experienced lower or higher incomes than predicted? In particular, can more exposure to weather anomalies help explain why some asset-rich households move below the poverty line and become income poor? In other words, were the *income poor* & *asset rich* more exposed to weather anomalies than the *income* & *asset rich*? Similarly, could *less* exposure to weather anomalies help explain why some asset-poor households move above the poverty line? In other words, were the *income rich* & *asset poor* less exposed to weather anomalies than the *income* & *asset poor*? As noted earlier, there are possible mechanisms (e.g., favorable access to forest resources) that can pull the

[14] The graph is generated by estimating the simple polynomial relationship between rainfall and mean income in the villages during the survey period (i.e. observed, not predicted income). It is generated using the *fpfit* command of Stata (fractional-polynomial prediction).

asset poor above the income poverty line, but weather anomalies can potentially prevent this from happening.

We look at rainfall only since the inter-annual variation is more pronounced than for temperature and therefore can be expected to have a larger impact on, for example, crop income. A deviation from normal rainfall will have different effects, depending on whether it is above or below the historical mean, and the level of the historical mean. In Table 5 we therefore distinguish between positive and negative deviations, and wet and dry areas. For reference, we also include the historical (30 year) rainfall (mean and SD).

For the dry areas, 17 % of the households (762 of 4,473) experienced rainfall that was more than 1 SD higher than the 30-year mean during the survey year. Close to 35% of this subset of asset poor have an income above the poverty line, as compared to close to 20% for the full sample. Also, in this subset (>1SD rainfall) we find a slightly lower share among the asset rich that are income poor (16% as compared to 21% for the two groups of asset rich households). While such simple comparisons are not a test of causality, these results are consistent with the possible effects discussed at the beginning of this sub-section: favorable weather conditions – more rainfall in dry areas – can help some asset poor households climb above the income poverty line. Also noteworthy, among those that had rainfall of more than 1SD above normal, the share of *income & asset rich* (71.5%) is almost twice the share in the full sample of dry area households (38.7%).[15] Among those experiencing lower than normal rainfall (<-1SD), there is no distinct pattern.

Table 5: Exposure to rainfall anomalies among households in dry and wet areas

	Income & asset poor	*Income rich & asset poor*	*Income poor & asset rich*	*Income & asset rich*	*Total*
Dry areas					
Means for poverty categories and total					
Mean 1981-2010 precipitation (mm)	1088	1097	1152	1176	1130
SD 1981-2010 precipitation (mm)	201	183	181	180	189
Precipitation anomaly in survey year (deviation/SD)	-0.04	-0.04	0.32	0.54	0.22
Distribution and # of household					
All households (HH)	41.0%	10.2%	10.1%	38.7%	4473
HH with rain > (mean + 1SD)	9.6%	5.1%	13.8%	71.5%	762
HH with rain < (mean - 1SD)	38.5%	13.2%	10.5%	37.8%	886
Wet areas					
Means for poverty categories					
Mean 1981-2010 precipitation (mm)	2315	2244	2175	2092	2201
SD 1981-2010 precipitation (mm)	339	305	283	268	300
Precipitation anomaly in survey year	0.09	0.15	0.23	0.34	0.21
Distribution and # of households					
All households (HH)	36.0%	12.1%	12.2%	39.6%	2856
HH with rain > (mean +1 SD)	33.3%	2.0%	5.1%	59.6%	198
HH with rain < (mean - 1SD)	62.4%	13.6%	4.7%	19.6%	213

For the wet areas, the picture is less pronounced. Only 14.4% had a deviation in rainfall of more than 1SD, as compared to 36.8% for the dry areas. Among asset rich households that

[15] We also did the analysis for more extreme deviations (>2SD), and the same patterns hold.

experienced at least 1SD above normal rainfall, a smaller proportion is in the *income poor & asset rich* category (8% vs. 24% for the full sample). There is no equivalent pattern for the asset poor with above normal rainfall, nor for the distribution across poverty categories for those experiencing less than normal rainfall.

In conclusion, the pattern is clearest for the dry areas: higher than normal rainfall during the survey year seems to have a positive effect on household income. In villages that had higher than normal rainfall, a higher share of the asset poor households is above the income poverty line.

4.3 Self-reported shocks

Our third research question shifts the focus from exposure to weather anomalies to exposure to self-reported shocks:[16] *Are self-reported shocks related to lower household income, and how does shock exposure vary across poverty categories?*

We know that there were no catastrophic events during the period of the study (Wunder et al. 2014b). Some of the survey villages experienced floods, while others experienced drought, attacks by wild animals and macroeconomic shocks. These events are considered as shocks, but they are indeed characteristic of rural economies in developing countries.

Shocks were grouped into three categories: *income shocks*, dominated by crop failures, which is often related to rainfall or temperature below/above normal; *asset shock*, including theft or death of livestock; and *labor shocks*, most commonly in the form of illness or death of a productive household member. An asset shock would normally imply a medium term income reduction. A loss of household labor would normally have income implications, although for some the impact might (partly) be offset by higher efforts from other household members. We focus on severe shocks in this section.

Table 6 gives the incidence of self-reported severe shocks during the year covered by the income survey. Overall, close to a quarter (24%) of the households did experience some type of shock during the survey year.

The *income & asset poor* have higher incidence of income shocks compared to the other households (14% vs. 9%). In other words, *income & asset poor* have more than 50% ((14-9)/9) higher probability to have experienced a severe income shocks. This difference is robust across wet-dry zones and across regions. The higher exposure to income shocks among the *income & asset poor* is consistent with a hypothesis that some asset poor might – due to the income loss in the survey year – be in the *income & asset poor* rather than the *income rich & asset poor* category. About one fifth of the asset poor are *income rich & asset poor*, for example, because they enjoyed a bumper harvest. An income shock can make it less likely for income poor to be in this category. The higher prevalence of shocks among the *income & asset poor* serves to illustrate how shocks can contribute to maintaining poverty.

[16] The correlation between weather anomalies and self-reported is very low, which might be due to the following reasons. First, the weather anomalies were relatively modest, and households have adaptive and coping mechanisms available. Second, a weather anomaly is not necessarily bad for household income, cf. the finding of higher income if rainfall increase in dry areas. Third, most of the shocks in poor rural economies are household-specific (idiosyncratic) while the weather anomalies are at the village level.

Table 6: Comparison of shock incidences during survey year across household categories (share of households that experienced shocks)

Shock	*Income & asset poor*	*Income rich & asset poor*	*Income poor & asset rich*	*Income & asset rich*	Test statistics[a]
Income shock	0.14	0.08	0.10	0.09	χ^2=16.08***
Asset shock	0.06	0.04	0.06	0.05	NS
Labor shock	0.12	0.11	0.12	0.13	NS
Any type of shock[b]	0.27	0.19	0.23	0.22	χ^2=15.71**
N	2863	801	801	2864	

*, **, *** Significantly different at 0.1, 0.05 and 0.01 level, NS=Not significant. [a] Kruskal-Wallis test of difference between the groups. [b] Share of households that experienced any of the above shocks.

We observe only small differences for the three other poverty groups. We expected a higher incidence of (income) shocks among the *income poor & asset rich* compared with the *income & asset rich*, i.e., that a higher prevalence of shock could help explain why some asset rich become income poor. This is not the case, and it might suggest that most of the asset rich households have sufficient means to deal with the shock. Further, the shocks – even if classified as severe – may not be sufficiently large to make the asset rich fall below the income poverty line.[17]

Overall, the findings suggest that income shocks – not unexpectedly – have a negative impact on observed income, and in particular for the asset poor. The results also suggest that the asset rich might have more means to reduce the negative impacts of an income shock.

5 Vulnerability across poverty categories

5.1 Household income and environmental reliance

Income and asset poor households are the most vulnerable, i.e., more sensitive to shocks with lower adaptation and coping capacities. In addition to the vulnerability due to their overall income and asset positions, we ask if there are some systematic patterns that make income and/or asset poor households more vulnerable to shocks, or, alternatively, make them in a relative better position to cope with shocks. We first look at the overall income composition, and the environmental reliance (income share) in particular. A high environmental reliance is suggestive that households have access to and the skills to use environmental resources as a possible coping mechanism (next section). This is confirmed in the econometric analysis of self-reported shocks in Noack et al. (2015): a high forest income share (at the village level) has a positive effect on households' choice to use forest or wild products as a coping strategy. Furthermore, there are reasons to believe that forest income – at least in the short/medium term - might be less sensitive to climate change compared to crop income, cf. section 2.2.

[17] To further test the impact of shock on observed income, we regressed the error term in the income prediction regressions (section 3.3), i.e. the difference between the observed and the predicted income, on different types of shock (dummies). The overall power of the model was weak (F-test), although the coefficient for income shocks was negative and statistically significant.

Next, we also see how income diversity differ across the poverty categories. High income diversity is generally assumed to make households less vulnerable to shocks, as they have not "put all the eggs in one basket". We summarize this in the following research question: *Do the income and/or asset poor households have higher environmental reliance and higher income diversity?*

The overall pattern found in the literature is that the income poor are more reliant on environmental income in a relative sense, but the non-poor are the most reliant in an absolute sense. This is confirmed by Table 7 (income shares) and Table A7 (absolute income). The *income & asset poor* have the highest environmental income share; 29% of their income is derived from natural environments compared to 25% for the *income & asset rich*.[18] As also noted in another analysis of the PEN data, the differences in income shares across income levels is less pronounced compared to what several earlier studies suggested (Angelsen et al. 2014).

Most of the environmental income is derived from forested areas (20%) rather than non-forested areas (7%). Among forest income, the three dominant categories are food (30.3%), woodfuel (35.2%) and structural and fiber products (24.9%). For the non-forest environmental incomes, the share is higher for food (48.9%) and lower for woodfuel (20.6%) and structural and fiber products (9.9%).

Crop income is the single most important income source in all groups (30-31%).[19] The livestock income share is lower for the *income & asset poor* (11%) compared to the other groups (13-16%), while this group rely more on wage income (17%) than the other groups (12%).

There are marked regional differences in the income composition (Table A7). While the sampled households in Latin America earn the highest share from environmental income, crops are the most important source of income in the other regions.[20] The income composition across poverty categories also varies more when we look at the regional income composition, as shown in Figure 2.

In the Latin American sites, the *income & asset poor* have the lowest environmental income shares, probably explained by the existence of a few valuable commercial forest products that generates high income and is able to lift some groups above the poverty line. In both Latin America and East Asia, the *income rich & asset poor* have the highest environmental reliance. In the case of East Asia, the *income poor & asset rich* have almost the same absolute environmental income as the *income & asset rich* (USD 587 vs. USD 611). The sub-samples in South Asia and Africa follow the global pattern, with the highest environmental income shares found among the two income poor groups.

[18] These are the average of the household level income shares, and are different from the shares obtained when first calculating average absolute income (top panel of table) and then calculate income shares.

[19] The income composition in the PEN sample could be compared with larger surveys of rural income in developing countries. Davis et al. (2014) uses data from 41 national household surveys in 22 countries. Agricultural crop income dominates in the African sub-sample with 55% as the simple mean (35% in our sample for Africa). Livestock makes up 9% (12 %), wage income 13% (9%) and non-farm self-employment 15%. The latter include a range of activities, including business and extraction of resources from the wild. Overall, compared with our PEN sample, our data have lower crop and higher environmental income shares. The difference is likely to be due to two factors, which we do not know the relative importance of: (1) the PEN sample is representative for rural areas with some access to natural forests, but not for rural areas in general; (2) the other household surveys have not sufficiently captured the environmental income, and/or it is classified as agricultural income. The income shares in the non-African (less representative) sample are markedly different: crop income has 25%, while wage employment makes up 34%.

[20] This should be interpreted with care, as the sample from Latin America is considered the least representative of its region. Several sites with high-valued forest products are included in the Latin American sample (e.g., Duchelle et al. 2014).

Table 7: Income composition across poverty categories

Variable name	*Income & asset poor*	*Income rich & asset poor*	*Income poor & asset rich*	*Income & asset rich*	Test statistics[a]
Absolute income (PPP USD AEU)	559	1 661	756	2 966	F=308.86***
Income shares					
Total	**1**	**1**	**1**	**1**	**-**
Cash	0.54	0.62	0.53	0.63	F=88.60***
Subsistence	0.46	0.38	0.47	0.37	F=88.60***
Crop	**0.30**	**0.31**	**0.31**	**0.31**	**NS**
Cash	0.10	0.13	0.10	0.14	F=36.03***
Subsistence	0.21	0.18	0.21	0.17	F=29.13***
Livestock	**0.11**	**0.16**	**0.13**	**0.13**	**F=15.90*** **
Cash	0.06	0.11	0.07	0.08	F=25.11***
Subsistence	0.05	0.05	0.06	0.05	F=2.62**
Forest env. inc.	**0.21**	**0.21**	**0.19**	**0.19**	**F=6.16*** **
Cash	0.07	0.10	0.08	0.09	F=10.12***
Subsistence	0.13	0.10	0.11	0.09	F=50.37***
Non-forest env. inc.	**0.08**	**0.06**	**0.09**	**0.07**	**F=20.25*** **
Cash	0.01	0.02	0.01	0.02	F=3.18**
Subsistence	0.07	0.04	0.08	0.05	F=48.96***
Plantation	**0.01**	**0.01**	**0.01**	**0.01**	**F=9.42*** **
Cash	0.00	0.00	0.00	0.00	F=7.46***
Subsistence	0.01	0.01	0.01	0.01	F=4.55***
Household business (cash)	0.05	0.07	0.08	0.10	F=50.39***
Wage (cash)	0.17	0.12	0.12	0.12	F=24.35***
Other (cash)	0.07	0.07	0.07	0.07	NS
Diversity					
Herfindahl index	0.40	0.46	0.40	0.45	F=57.73***
Share of hh with index>0.6	0.10	0.20	0.09	0.17	F=35.66***
N	2863	801	801	2864	

*, **, *** Significantly different at 0.1, 0.05 and 0.01 level. NS=Not significant. [a] One-way ANOVA. [b] Mean shares are calculated by taking the mean of household shares.

Splitting total and sectoral incomes between subsistence and cash income also gives a more distinct pattern between the income categories, cf. Table 7. The average cash income share in the full sample is 58%.[21] There is a marked difference between the two income poor groups; the income rich have cash shares of 62-63% compared with 53-54% for the two income poor groups. Thus there is a significant positive correlation between income level and the cash income share (r=0.22[22]). This pattern is due to higher cash shares for key income sources: crop, livestock and forest income, rather than higher shares of pure-cash incomes such as business and wage.

[21] Note that this is the average share across households, and not the share of village economy that is cash (which is higher, as richer households tend to have a higher cash share).
[22] r is the simple (Pearson) correlation coefficient.

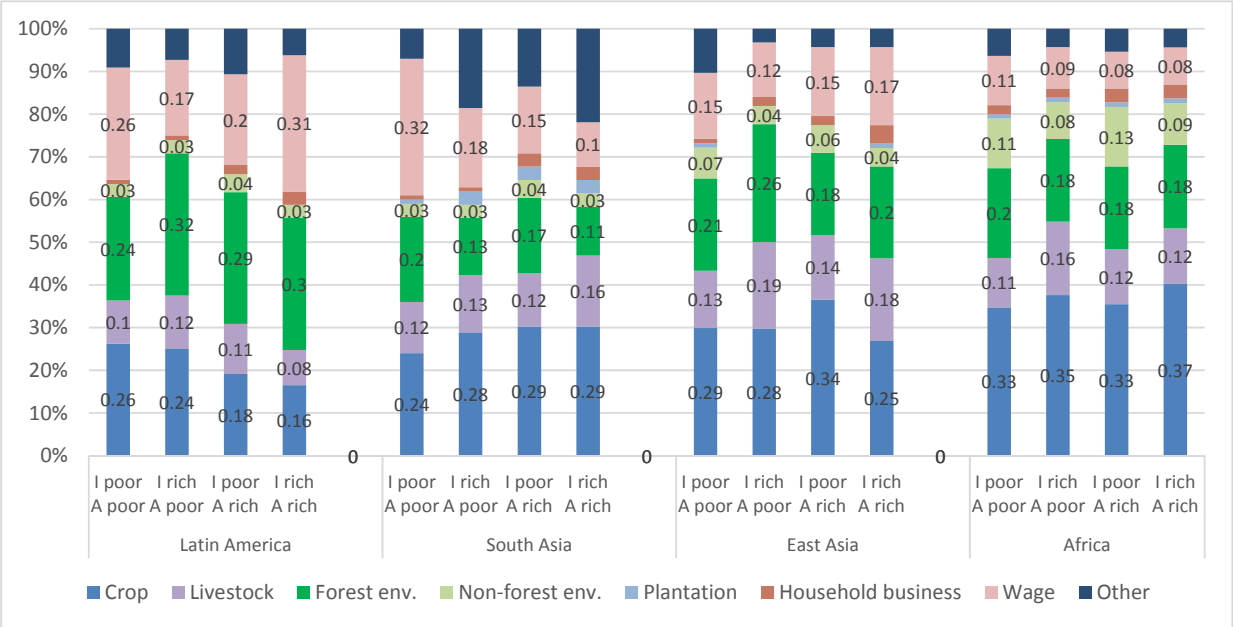

Figure 2: Income composition (shares) across regions and poverty groups

Three quarters of environmental income is used for household consumption. Income rich households earn a significantly higher share of the environmental income as cash (t=4.75[23]); 17% and 30% for the income rich groups compared with 21% and 22% the income poor groups. Also for environmental income, higher income is related to higher market engagement.

Yet, poor households also rely heavily on markets for their livelihoods. Among the *income & asset poor*, only 9% have a subsistence income share above 80% (with 46% of their income being from crops). At the other end among the *income & asset rich*, only 29% have a cash income share of above 80%. Thus although there is a correlation, any stereotypical image of poor mainly producing for subsistence and better-off households mainly for markets is misleading.

Finally, we consider income diversification as measured by the Herfindahl (Simpson) diversity index, calculated as the sum of the squared sectoral income shares.[24] A lower value means a more diverse income portfolio. The two income poor groups have more diverse income portfolios, with a Herfindahl index of 0.40, compared with 0.45-0.46 for the two income rich groups (Table 7). The correlation between income level and diversity is relatively strong (r=0.22): higher income is associated with specialization.

From a vulnerability perspective, it might also be relevant to look at households that are heavily dependent on just one income source. The last row of the table gives the share with a diversity index greater than 0.6 (which is set somewhat arbitrary), i.e., those that pursue a more

[23] Two-sided t-test.

[24] The index in sensitive to the how many sectors are specified, prohibiting comparisons across studies with different sector specification. We use the following seven sectors: crop, livestock, forest, non-forest environmental income, business, wage and other. If the income is just from one source, the value is 1; if the income is evenly spread across the seven sectors, the value is 0.14.

specialized income strategy.[25] As expected, within the two high income groups a higher share pursue such as strategy. In particular, among the *income rich & asset poor*, 20% get most of their income from a single source. Specialization seems to be a strategy for moving out of income poverty for asset poor households.

High income diversity is commonly viewed as part of a risk management (adaptive) strategy to deal with risk. The higher diversity found among the income poor should, *ceteris paribus,* make them less sensitive to shocks. Yet, income diversity is only one aspect of vulnerability.[26] A high diversity can also be viewed as large groups of households not having access to income from the most profitable activities, which would have helped them increase overall income and move above the poverty line.

5.2 Self-reported responses to shocks[27]

The PEN data set contains detailed information on self-reported responses to any shocks that the household faced during the survey year. Collecting more products from forests and other natural habitats is one option, and we ask: *How important is increased harvesting of forest and other wild products as a coping strategy after a shock, and how does this strategy vary across households, and type and severity of the shock?*

5.2.1 Coping strategies across types of shocks

Households were asked about how they coped with the shock, and could rank up to three responses in order of importance. We focus on the top-ranked response, unless otherwise stated, but discuss the full range of responses at the end of this section.

Figure 3 shows how households responded to the three main categories of shocks. We have included the "did nothing in particular" response. For shocks that have reduced income this could be interpreted that the household has lowered consumption and/or reduced savings. Overall, "did nothing" is the most common response (20%). The most frequently mentioned among the active coping response is to take on extra casual (wage) labor (15%) or use household savings (13%), followed by harvest/sell more agricultural products[28] (10%), and harvest more products from forest and other natural habitats (9%).[29]

There is a large and interesting variation in the coping strategies across different types of shock. More wage work is the most common response after an income shock. Spending household savings is the most common one after a labor (including health) shock, which is not surprising as illness prevents the household member from taking up extra work. In almost half of the cases when households experienced an asset loss they did nothing in particular, probably because this might not involve an immediate income shortfall. Getting assistance from friends, relatives or an organization

[25] To illustrate that degree of specialization implied, the following income composition would create a Herfindahl Index of 0.6: 77% of the income is earned from one activity, while the remaining 23% is spread equally over the six other income categories.
[26] As noted by Dercon (2002), the degree of diversification is an incomplete measure of diversification. It does not take into account the magnitude of risk for the difference activities, not the covariance between income sources (e.g., in response to climate variability).
[27] See also Wunder et al. (2014) for an analysis and discussion of the safety net function of forests products, also based on the PEN data.
[28] This strategy might also entail reduced food consumption, e.g., sell more of food stored to cover cash expenses.
[29] This category is the aggregate response of two codes in the questionnaire: "Harvest more forest products" and "Harvest more wild products not in the forest".

is much more common after labor shocks than for other shocks, possibly because those tend to be more idiosyncratic than other shocks, and because some shocks involve more social support.

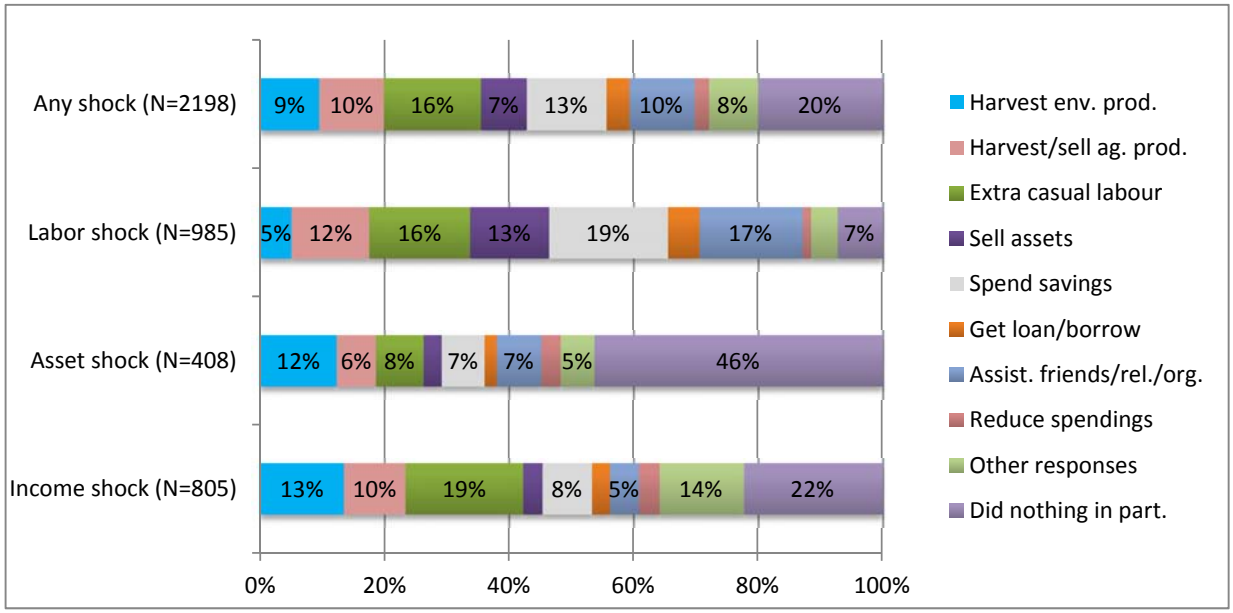

Figure 3: Self-reported responses to household shocks by shock type (percentage distribution of the highest ranked response)

"Harvesting more environmental products"[30] as a coping strategy also varies across the different types of shocks. It is ranked second among income shocks (13%), and among these, it is mentioned more frequently for wage loss than for crop failure. Losing employment would free up family labor that can be used for, for example, harvesting more forest products. At the other extreme, harvesting more environmental products is least mentioned as a coping strategy for health shocks, for reasons already mentioned.

In the following we focus on income shocks, partly they have a more immediate effect on the household compared to, for example, an asset shock, and partly because they are linked to having lower than predicted income if households cannot invoke effective coping strategies.[31]

5.2.2 Coping strategies across poverty categories

The differences in coping strategies across the four groups are depicted in Figure 4. Harvesting more environmental products are mentioned as the primary coping strategy by 13.4% of the households that have experiences income shocks, or 17.3% among the active coping strategies (i.e. excluding the "did nothing" response). There are some noteworthy differences, which points to how access to various coping mechanism co-determine the welfare impact of shocks.

[30] "Harvesting more environmental products" is the sum of two responses, harvesting more forest products and harvesting more wild products from non-forest areas. Forest products make up 87% of the combined responses.
[31] Income shocks are predominantly crop failures, which often is related to extreme weather events. Climate change could potentially also have impacts on assets (assets shock), e.g. on cattle mortality, and on human health (labor shocks) due to prevalence of diseases.

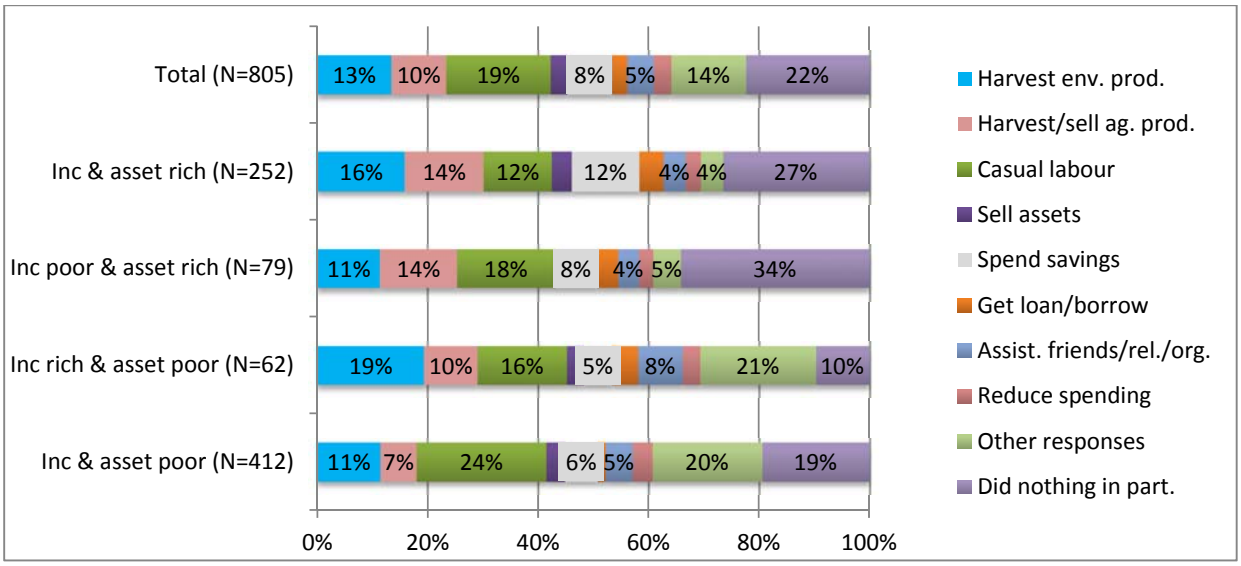

Figure 4: Self-reported response to income shocks across household categories (percentage distribution of the highest ranked response)

Harvesting more environmental products is most common among the two income rich groups, e.g., 19% of the income rich and asset poor has this as the primary coping strategy as compared to 11% for the *income & asset poor* households. Those households that have access to coping based on environmental resources seem *less* likely to fall into (or remain in) income-poverty when experiencing an income shock. This is consistent with a hypothesis of environmental income serving as a safety net.

The *income rich & asset poor* also poor is also different from the other groups by having the lowest "do nothing" response (10% compared to 22% for all groups). This group therefore seems to pursue more active coping strategies, either by being more entrepreneurial, by having better access to coping mechanism, or a combination of the two. Thus in spite of the income shock they have higher than predicted income. This can be contrasted with the group that have lower than predicted income, the *income poor & asset rich*. A third of these households state "did nothing" as their response to an income shock, something which could help explain why they fell below the poverty line.[32]

More generally, different household characteristics have an impact on what coping mechanisms a household has available. Income generating coping strategies[33] are more actively pursued by the asset poor (62%) than the asset rich groups (47%). The asset rich groups rely more on asset liquidation (including using savings) as a way to cope (18% as compared to 11% for the asset poor groups). The availability and quality of wild resources from the forest and other areas vary across locations, as does the access to markets that can convert these products into cash.

[32] We also looked at all coping responses, i.e., included those ranked second and third in households' self-reported responses. The distribution of all responses are similar to the primary responses, with one exception. The share mentioning "harvest/selling more agricultural products" is about twice as high for the second and third ranked responses, as compared with the primary response. Selling more agricultural products (and by extension: reducing household food consumption) is a strategy to deal with cash shortfall to meet priority expenditures (key food, school fees, medicines, etc.).

[33] Income generating strategies include harvesting environmental products, harvesting and selling agricultural products, wage income (casual labor) and "other strategies". We included the latter as many of these are income generation such as starting small business and planting new crops.

The PEN data distinguish between moderate and severe shocks, and so far we have focused on severe shocks, for two reasons: first, a critical aspect of future climate change is the higher frequency and severity of extreme events; second, looking at the data and frequency of shocks, moderate shock might by some respondents be interpreted as what could more appropriately be classified as normal income variations. For example, while 11% of the households reported a severe income shock, 31% reported a moderate income shock, bringing the total incidence of income shocks to 42%. Yet, a brief analysis can shed light on how different coping mechanisms depends on the magnitude of the shock.

A comparison of the most common coping responses by severity of the shock, across poverty categories, is given in Figure 5. Harvesting of environmental products is more frequently mentioned for the moderate shocks compared to the severe ones: 17% vs. 13%. This pattern holds across all poverty categories. Among the active coping responses (i.e. excluding "do nothing"), 22% stated that harvesting more forest or other wild products is their primary response to a moderate income shock.

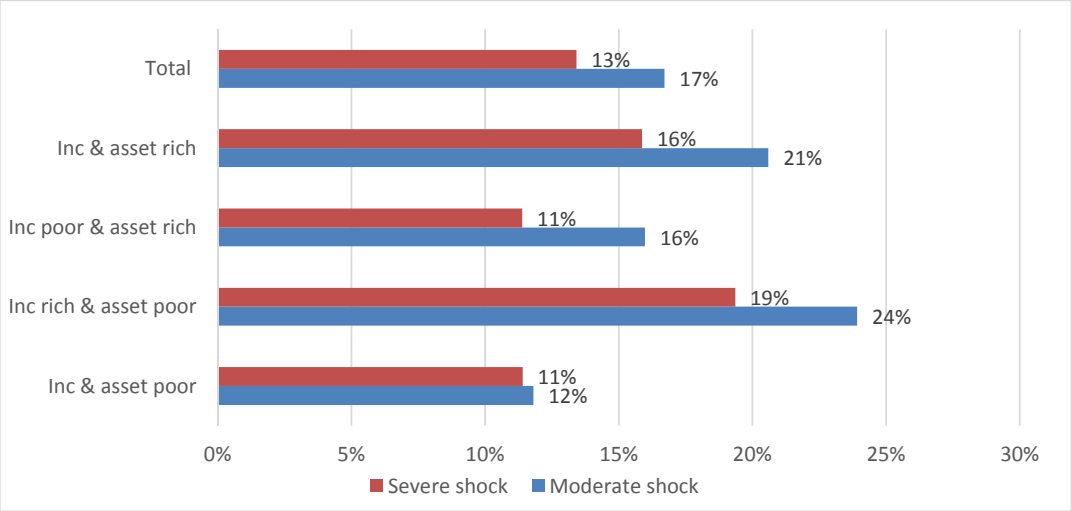

Figure 5: Share of households using harvesting environmental products as primary coping strategy after an income shock

Harvesting more environmental products is not "quick and easy cash" in response to a shock. If it was, it would have been fully exploited by the household even without experiencing a shock. Rather, the result suggests that it is particularly suitable for dealing with moderate income shortfalls.

5.3 Access to forest resources and resource degradation

Environmental income plays an important role in the livelihoods, both to support current consumption, reduce vulnerability and potentially make some asset poor households move above the poverty line. It is therefore relevant to see how the physical access to environmental resources vary and how the resource base is changing. If rural households, particularly the poorest, experience a decline, this might jeopardize the future potential for environmental income to buffer the impact of climate change. We address this by asking: *Do the income and/or asset poor have poorer physical access to forest resources and is their resource base more exposed to degradation?*

As a measure of physical access to forest, we use the tree cover in each of the sampled villages. Based on the forest transition hypothesis (below), we expect to see a negative correlation between forest cover and income, basically because better market access as an underlying factor both makes forest conversion more profitable and improve income opportunities.

Overall, there are small differences in tree cover across the different household categories, although the *income & asset rich* tend to live in villages with slightly higher tree cover (Table 8), particularly for wet forest areas in East Asia. In Latin America, we have a slightly opposite picture: forest cover is lower for the *income & asset rich*. In Africa, where most of the sites are in the dry zones, there is no clear picture. Overall, we find limited evidence in support of an hypothesis that the poorest households live in villages with more forests, which then would help them cope with climate (or other) shocks.

This finding might be surprising. The forest transition hypotheses (Mather 1992) suggests that forested areas (or even countries) might go through distinct stages, from a situation with high forest cover (*core* forests), to a *frontier* stage with high deforestation rates, to a stabilization phase with a *mosaic* landscape. The core areas are the characterized by poor market access, poorly developed infrastructure and (therefore) relatively high poverty (Chomitz et al. 2007, Angelsen and Rudel 2013). We should therefore expect a negative correlation between household income and forest cover, but find only weak correlations between household income and tree cover within the regions.[34]

We have two possible explanations of this finding. First, there might be some selection bias in the sample, i.e., sampling of high forest cover sites with valuable commercial forest products. Forest income – both absolute and relative – is strongly correlated with forest cover (r=0.27), and this seems to compensate for the remoteness associated with high forest cover. Second, the forest transition hypotheses does not seem to describe well the pattern in dry forest area in developing countries, but typically has rainforest frontier contexts as its point of reference.

Table 8 also gives the *loss* of tree (forest) cover in the villages during the period 2000-2010, which represent processes of both deforestation and forest degradation. We have no *a priori* expected signs: high forest loss could signal intensive use and corresponding high forest incomes, but could also indicate degrading resources with shrinking incomes.

For the full sample, the *income & asset rich* have lower rates of forest loss than the other groups, but with large variation across zones and regions. In the dry areas, the *income & asset poor* experience much higher forest loss compared to the other poverty categories. In contrast, the *income & asset rich* tend to live in villages with a stable forest cover. In wet areas, the opposite is true: the *income & asset poor* have on average only about half the loss in their villages compared with other poverty groups.

The differences between wet and dry areas is linked to regional differences. In the African sub-sample, dominated by dry sites, the rate of forest loss during 2000-2010 for the *income & asset poor* was four times higher compared to the rate for the *income & asset rich*. Thus for our largest sub-sample, we can clearly conclude that *income & asset poor* experience much higher forest loss than the other groups, in line with our hypotheses. In the two Asian regions, the pattern is different, with the

[34] For the full sample, the Person correlation coefficient is positive (0.16), but this is largely due to a "Latin America" effect: the Latin American sites tend to have both higher income and higher forest cover. Also, recall that the poverty lines as median, regional incomes, so this effect vanished in when looking at poverty categories.

income & asset poor in Asia was residing in villages that on average experience a gain in forest cover in the during the period 2000-2010.

Table 8: Village tree cover and tree cover change

	Income & asset poor	*Income rich & asset poor*	*Income poor & asset rich*	*Income & asset rich*	Total
Tree cover (% of land area) [35]					
Forest type:					
Dry	23.6	22.9	24.0	24.3	23.9
Wet	44.3	41.7	44.1	48.1	45.5
Region:					
Latin America	62.1	62.3	63.7	58.7	60.9
South Asia	25.5	29.2	32.1	30.5	28.6
East Asia	32.4	35.4	36.8	42.0	36.9
Africa	25.6	23.8	25.4	26.8	25.9
Total	31.1	31.0	32.8	33.7	32.3
Tree cover loss (% of land area, 2000-2010)[36]					
Forest type:					
Dry	1.79	0.73	0.50	0.08	0.89
Wet	1.74	3.35	3.97	3.20	2.78
Region:					
Latin America	1.35	2.24	1.77	1.21	1.42
South Asia	-0.70	-0.67	0.78	1.28	0.24
East Asia	1.25	5.49	5.96	3.83	3.39
Africa	2.64	1.08	0.81	0.60	1.48
Total	1.77	1.86	2.02	1.31	1.63

Any positive correlation between poverty and forest loss is a classic example where causality could run both ways: do poor people overexploit environmental resources, or do shrinking environmental resources make people poor? Fully exploring this would preferably be using panel data, but the following points are indicative. The strong association between forest loss and structural poverty in the African sub-sample, is consistent with the large literature on a poverty-environment nexus on the continent (e.g., Duraiappah 1998). Relatedly, wet forest tend to have more commercially valuable products, timber in particular. This increases both the potential to lift some households out of poverty (cf. the high forest loss among *income rich & asset poor* in Latin America) and makes forests more attractive to exploitation by outsiders. This could help explain the negative association between structural poverty and forest loss in wet areas.

[35] Our definition of forest cover is tree canopy cover within the village (a circle of 5 km radius), and not the standard FAO definition of forest as an area with min. 10% tree canopy cover. Using that definition would yield significantly higher forest cover figures. Our definition is more suitable for the purposes of this paper, i.e., as a measure of forest resources available.

[36] The typical deforestation measure is net forest loss as a percent of forest area, not land area. The rates of forest loss in the table are therefore much smaller than those typically reported. For example, with a forest cover in dry area of 24%, a loss of 0.89 must be multiplied by more than 4 to get the loss as a share of forest area.

Related to our focus on vulnerability, the high forest loss in areas where the *income & asset poor* – the most vulnerable group - in dry and in African sites is a matter of concern. Given the strong correlation between forest cover and forest income and reliance,[37] this suggests that a major source of income and a buffer against climate and other shocks is under threat.

Finally, the higher tree loss in poor villages in dry zones could also be linked to higher exploitation of forest resources due to higher exposure to climate variability. To check whether tree cover loss might be driven by high climate variability, we regress tree cover loss during the period 2000-2010 as a function of climate parameters, i.e. the mean and standard deviation of the precipitation and temperature over the period 1980-2010. We control for tree cover and regions. The results are presented in Table 9.

Table 9: Regression model for tree cover loss and climate[38]

	Dry areas		*Wet areas*	
	Coefficient	*Std.errors*	*Coefficient*	*Std.errors*
Precip mean (mm)	0.004	0.003	- 0.000	0.002
Precip std.dev.	0.030*	0.017	0.002	0.007
Temp mean (C)	-0.323***	0.088	1.548***	0.281
Temp std.dev.	17.418***	3.732	60.944***	13.549
Tree cover (share)	-0.632***	0.152	0.409***	0.142
Tree cover squared	0.012***	0.003	-0.004***	0.001
Latin America[1]	(omitted)		-4.213*	2.421
South Asia[1]	-7.680**	3.143	- 3.054	2.637
East Asia[1]	-5.180***	1.920	- 0.120	2.562
Constant	- 2.917	4.229	-63.824***	11.860
R-square	0.276		0.252	
N	164		152	

[1] Regional effect as compared with Africa (default region).

For dry areas, both higher rainfall and temperature variability is correlated positively with more forest loss. For wet areas, only rainfall variability is significant. While such correlations does not give any proof of causality, the results are consistent with an hypothesis of higher climate variability causing more fluctuations in incomes, and exploitation of forest – both land clearing for agriculture and harvesting of trees – is one strategy to deal with the income shocks generated by climate extremes.

6 Summary and policy implications

6.1 Exposure to climate conditions and weather anomalies

The income poor households tend to live in relatively more extreme climate conditions, as measured by the mean precipitation and temperature over the 30-year period (1981-2010). In the dry areas the income poor households on average live in (even) dryer and warmer villages, while in the wet areas they tend to live in (even) wetter and colder sites. In terms of climate variability over the 1981-2010 period, in both wet and dry areas the income poor households tend to live in villages that

[37] For the African sub-sample, the correlation between forest reliance and forest cover is 0.36.

[38] Three cover loss is the reduction in the tree cover as share of total land area for the period 2000-2010. The model is run at village level, using standard OLS.

experience larger precipitation variability. The differences are significant and quite pronounced, e.g., the rainfall variability (standard deviation - SD) in wet areas is 17% higher for income poor households.

The relationship between weather anomalies (in the survey year) and household incomes is more nuanced. Higher-than-normal rainfall in dry areas seems to have had a positive effect on income. For example, in villages that have had 1SD more rainfall than normal, there are relatively more *income rich & asset poor*, and fewer *income poor & asset rich* households. For other links between weather anomalies and the poverty categories the pattern is less clear, and this might be explain by several factors. First, the weather anomalies experienced in the study areas during the survey year were moderate compared to the possible changes in rainfall and temperature in climate scenarios. Second, fluctuations in rainfall (and temperature) are part of the reality, and rural households have over time developed adaptation and coping strategies to minimize negative impacts. These strategies may include more forest exploitation, and we find a positive correlation between tree over loss and exposure to climate extremes. Third, deviations from historical means of rainfall or temperature are not necessarily harmful for household income, for example, above-normal rainfall of in the dry areas seems to have had a beneficial effect on household incomes. Fourth, the results are a useful reminder that the predicted climate changes will hit all, whether poor or less poor. Also, within our sample most households are poor in a macro-perspective.

Considering self-reported shocks, *income & asset poor* have 50% higher probability to have experienced a serious income shocks, compared with the three other poverty categories. We do not find any higher incidence of income shocks among the *income poor & asset rich*, as hypothesized. Overall, the negative income effects are smaller than expected, and this suggests that households have coping strategies available that dampen the impacts of shocks.

6.2 Adaptive and coping capacity

The adaptive and coping capacity of households is determined by a number of factors, in addition to the absolute income and asset level and composition. All households have quite diverse income portfolios, both reflecting deliberate risk management (adaptive) strategies as well as seasonal variations in income opportunities. The income poor households have relatively more diverse income portfolios, which should make them less vulnerable. However, this also reflects that higher income is associated with specialization in higher return activities. High diversity therefore signals a lack of access to profitable activities.

Climate change is going to affect the income potential of different sectors differently, with large variations across locations. At least for short term impacts, one might hypothesize that harvesting based on stocks of biomass (e.g. wood and fiber from forests) rather than flows of natural resources (wild food and crops) are less sensitive to climate variability. Moreover, high environmental reliance indicates access to environmental resources and therefore better chances to draw more on these to cope with shocks. Across the four poverty categories, environmental income shares vary between 25% and 29%, with a positive correlation between income level and environmental reliance.

Self-reported coping strategies against income shocks suggest a diverse set of responses, from seeking alternative income opportunities, selling assets and using saving, and reducing consumption. Following income shocks, harvesting more products from forest and other natural habitats is the second most common coping response, after seeking addition wage income. The environmental strategy is relative more used by the two income rich groups. About one-fifth of the

income rich & asset poor has environmental product harvesting as the primary coping strategy as compared to about one-tenth for the *income & asset poor* households, which is in line with the hypothesis of forest playing a safety net and poverty-preventing role for some groups after an income loss.

We also find evidence of the environmental strategy being relatively more important for coping with moderate than severe income shocks. Among the active strategies (ignoring the "do nothing" response), 22% of the respondents stated that harvesting more environmental products is their primary response to a moderate income shock. Given the *de facto* open or easy access to forests and other natural habitats, this is an option available to many households. At the same time, the potential for significantly higher income from environmental resources, following an income shortfall, also has its limits. Harvesting more is a labor-intensive strategy compared with, for example, liquidating assets. Limited market access often constrain the opportunities for converting forest products into cash.

Looking at forest loss in the village during the period 2000-2010, there are huge differences across types of forests and regions. In dry forests in general and in Africa – the poorest region, the *income* & *asset poor* have experienced far greater forest loss over the past decade than other groups. Causality can run both ways, but this result is consistent with theories on a poverty-environmental degradation nexus. Yet, the simple fact that degradation in dry forests and in Africa is highest in the areas where the poorest live is a worrying result. An important source of both regular income and safety net is shrinking.

While environmental income serves several functions, the IPPC AR5 also warns that continuous "warming and changes in precipitation are increasing tree mortality in a wide range of forest systems, acting via heat stress, drought stress, pest outbreaks, and a wide range of other indirect impact mechanisms" (Scholes et al. 2014, 303). In the long term, the ecosystems' capacity to provide the wide range of products the rural households rely on is at risk. In this scenario, the poorest would be more exposed and more vulnerable than the better-off groups.

6.3 Policy relevance

The challenge of sustainable use of forest and other natural environments is twofold: ensure resource access for the poor, while limiting long-term degradation and protecting the biophysical resource. In a worst case scenario, removing incomes that make up more than one-fourth of total household income will increase and deepen poverty profoundly. Furthermore, environmental income plays a stabilizing role in rural economies and for individual households. Maintaining this resource base, therefore, provides win-win opportunities for the long term. The PEN data, demonstrating that such a significant proportion of household income is derived from environmental resources, suggest that the win-win potential is larger than commonly perceived.

One challenge for policy designers and decision-makers is to distinguish between destructive and non-destructive uses. This concerns both the type of harvests (e.g., cutting down living trees vs. collecting dead branches for firewood) but also the level of extraction (i.e., to keep harvest within the natural regeneration). Another challenge concerns which groups should have access to the resources. A "fence and fine" approach will restrict the poorest access to natural resources. Permitting uses dominated by the poor, e.g., subsistence uses that have limited degrading effects on the resource base, may reduce the negative livelihoods impacts of conservation policies or projects. At the same time, forest clearing is increasingly driven by large-scale, commercial actors (Rudel 2007), also suggesting that the nature of the conventional poverty-environmental trade-off has

changed or even reversed in some contexts. Such increasingly dominating drivers threaten both local livelihoods and the natural resource base.

To the extent climate change over time also reduce the availability of (and access to) environmental resources, the most vulnerable will be hit disproportionally hard. Climate change may reduce their role as a steady source of income, as a safety net for some groups, and as a stepping-stone for some asset-poor households to move above the income poverty line.

The distinction between structural and stochastic income is valuable for understanding vulnerability and for targeting of social protection. The focus in vulnerability analyses should shift from observed "snap-shot" income to predicted income based on an (augmented asset) approach, in order to minimize the effect of temporal income fluctuations.

The distinction between dry and wet forests has revealed distinct patterns, and suggests that dry forest needs special attention. The poorest households in these areas, predominantly in Africa, are among the poorest in a global perspective, are (already) exposed to more extreme climate conditions, and suffer the highest forest loss, which over time will undermine their opportunities to derive income from forest resources. Moreover, "continuing changes in precipitation, temperature, and carbon dioxide (CO_2) associated with climate change are very likely to drive important future changes in terrestrial ecosystems throughout Africa" (Niang et al. 2014, 1215). Reducing the vulnerability arising from such multiple stressors represents one of the main policy challenges for the coming decades.

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7 Appendices

7.1 Variables included in the regression model to predict income

Table A 1: List of variables included in the models to predict household income

Variable	*Description*
Physical capital	
Agricultural land	Agricultural land owned, in hectares and log-transformed
Livestock	Livestock owned, in tropical livestock units and log-transformed
Business	Dummy indicating if the hh* has a hh business
Human capital	
Labor available in household	Number of male and female elders, adults and children in the hh
Age of the household head	Age in years and squared term to account for non-linear effects of age
Female headed household	Dummy indicating whether the head of hh is female
Education	Education of the hh head (in years)
Skills	Dummy indicating if any in the hh earn salary from wage labor (proxy)
Financial capital	
Household implements	Value of hh implements (in PPP adjusted USD and log-transformed)
Savings	Value of savings in banks and informal institutions, physical non-productive assets and outstanding debt (in PPP adjusted USD and log-transformed)
Social capital	
Born in village	Dummy indicating if hh head was born in the village
Majority ethnic group	Dummy indicating if hh head belongs to largest group in the village
Distance	Distance from the hh to the village center (in minutes walking)
Natural capital	
Proximity to forest	Distance to the forest (in minutes walking time from the household)
Weather variables	Mean precipitation and temperature in the village between 1981-2010
Infrastructure (village level)	
Electricity	Share of households in the village with access to electricity
Market integration	Share of cash over total income in the village
Political capital	Country dummies

*hh=household

7.2 Descriptive statistics, total and by region

Table A 2: Summary statistics regression variables (Global sample, N=7329)

	Mean	Std.dev	Min	Max
Household level variables				
Total household income (USD PPP)	5 872	14 195	0	852 982
Number of male adults (15-65 yrs)	1.68	1.18	0	10
Number of female adults (15-65 yrs)	1.67	1.18	0	21
Number of male elders (above 66 yrs)	0.26	0.48	0	2
Number of female elders (above 66 yrs)	0.13	0.35	0	3
Number of male children (0-14 yrs)	1.32	1.38	0	10
Number of female children (0-14 yrs)	1.26	1.35	0	10
Agricultural land owned (hectares)	4.91	12.85	0	612
Livestock owned (TLU)	4.23	10.96	0	298
Household has own business (1 yes)	0.36	0.48	0	1
Age of household head (years)	45.67	14.45	14	111
Female headed household (1 female)	0.12	0.32	0	1
Education household head (years)	4.10	4.03	0	18
Household has wage income (1 yes)	0.61	0.49	0	1
Financial assets (USD PPP)	1 685	5 673	0	166 666
Hh head born in village (1 yes)	0.55	0.50	0	1
Hh head belongs to largest ethnic group (1 yes)	0.74	0.44	0	1
Distance village center (minutes walking)	0.39	0.55	0	5
Distance forest (minutes walking)	0.57	0.72	0	5
Village level variables				
Village mean precipitation (1981-2010)	1 547	628	658	3 667
Village mean temperature (1981-2010)	23.47	4.50	9	29
Electrification (share of hhs with electricity)	0.23	0.37	0	1
Village market integration (mean cash/total inc.)	0.18	0.08	0.03	0.69

Table A 3: Summary statistics for variables included in the regression models. Latin America sample (N=848)

	Mean	Std.dev	Min	Max
Household level variables				
Total household income (USD PPP)	15 099	16 076	646	125 587
Household size (AEU)	3.75	1.77	1	11
Number of male adults (15-65 yrs)	1.70	1.24	0	10
Number of female adults (15-65 yrs)	1.50	1.16	0	8
Number of male elders (above 66 yrs)	0.31	0.52	0	2
Number of female elders (above 66 yrs)	0.16	0.39	0	2
Number of male children (0-14 yrs)	1.15	1.24	0	6
Number of female children (0-14 yrs)	1.10	1.29	0	8
Agricultural land owned (hectares)	10.49	18.00	0	301
Livestock owned (TLU)	8.49	21.05	0	254
Household has own business (1 yes)	0.23	0.42	0	1
Age of household head (years)	44.56	14.28	18	92
Female headed household (1 female)	0.07	0.26	0	1
Education household head (years)	5.57	3.92	0	18
Household has wage income (1 yes)	0.78	0.41	0	1
Financial assets (USD PPP)	4 105	9 898	0	129 253
Hh head born in village (1 yes)	0.33	0.47	0	1
Hh head belongs to largest ethnic group (1 yes)	0.83	0.37	0	1
Distance village center (minutes walking)	0.49	0.69	0	5
Distance forest (minutes walking)	0.65	0.96	0	5
Village level variables				
Village mean precipitation (1981-2010)	2 272	537	1 729	3 667
Village mean temperature (1981-2010)	23.41	3.15	15	27
Electrification (share of hhs with electricity)	0.47	0.44	0	1
Village market integration (mean cash/total inc.)	0.26	0.08	0.06	0.69
Country level variable				
GDP per capita (2010 USD)	3 887	2 248	1 935	10 978

Table A 4: Summary statistics for variables included in the regression models. South Asia sample (N=1094)

	Mean	Std.dev	Min	Max
Household level variables				
Total household income (USD PPP)	5 221	5 228	206	112 471
Household size (AEU)	3.74	1.45	1	11.90
Number of male adults (15-65 yrs)	1.77	1.10	0	7
Number of female adults (15-65 yrs)	1.70	0.98	0	8
Number of male elders (above 66 yrs)	0.31	0.52	0	2
Number of female elders (above 66 yrs)	0.14	0.36	0	2
Number of male children (0-14 yrs)	0.89	0.98	0	6
Number of female children (0-14 yrs)	0.79	0.95	0	5
Agricultural land owned (hectares)	3.78	7.40	0	79
Livestock owned (TLU)	4.14	8.33	0	182
Household has own business (1 yes)	0.24	0.42	0	1
Age of household head (years)	49.38	14.81	14	97
Female headed household (1 female)	0.11	0.32	0	1
Education household head (years)	2.49	3.69	0	15
Household has wage income (1 yes)	0.78	0.41	0	1
Financial assets (USD PPP)	3 010	7 770	0	118 992
Hh head born in village (1 yes)	0.78	0.42	0	1
Hh head belongs to largest ethnic group (1 yes)	0.82	0.38	0	1
Distance village center (minutes walking)	0.40	0.54	0	4
Distance forest (minutes walking)	0.58	0.42	0	3
Village level variables				
Village mean precipitation (1981-2010)	1 882	673	1 177	3 197
Village mean temperature (1981-2010)	21.63	6.83	9.05	27.55
Electrification (share of hhs with electricity)	0.42	0.41	0	1
Village market integration (mean cash/total inc.)	0.19	0.05	0.11	0.34
Country level variable				
GDP per capita (2010 USD)	833	320	596	1 417

Table A 5: Summary statistics for variables included in the regression models. East Asia sample (N=1297)

	Mean	Std.dev	Min	Max
Household level variables				
Total household income (USD PPP)	5 348	5 561	0	87 162
Household size (AEU)	3.41	1.16	1	10
Number of male adults (15-65 yrs)	1.59	0.95	0	7
Number of female adults (15-65 yrs)	1.53	0.86	0	7
Number of male elders (above 66 yrs)	0.27	0.47	0	2
Number of female elders (above 66 yrs)	0.12	0.34	0	2
Number of male children (0-14 yrs)	0.85	0.98	0	7
Number of female children (0-14 yrs)	0.78	0.92	0	4
Agricultural land owned (hectares)	2.03	3.13	0	52
Livestock owned (TLU)	2.24	2.60	0	33
Household has own business (1 yes)	0.26	0.44	0	1
Age of household head (years)	43.88	12.93	18	90
Female headed household (1 female)	0.10	0.30	0	1
Education household head (years)	4.96	3.51	0	17
Household has wage income (1 yes)	0.61	0.49	0	1
Financial assets (USD PPP)	1 846	3 883	0	49272
Hh head born in village (1 yes)	0.51	0.50	0	1
Hh head belongs to largest ethnic group (1 yes)	0.89	0.32	0	1
Distance village center (minutes walking)	0.25	0.32	0	2
Distance forest (minutes walking)	0.43	0.39	0	4
Village level variables				
Village mean precipitation (1981-2010)	1 981	607	1144	3238
Village mean temperature (1981-2010)	25.29	2.93	19	28
Electrification (share of hhs with electricity)	0.47	0.42	0	1
Village market integration (mean cash/total inc.)	0.23	0.08	0.11	0.41
Country level variable				
GDP per capita (2010 USD)	2 114	1 404	783	4 433

Table A 6: Summary statistics for variables included in the regression models. Africa sample (N=4090)

	Mean	Std.dev	Min	Max
Household level variables				
Total household income (USD PPP)	4 298	16 436	31	852 982
Household size (AEU)	4.41	2.17	1	20
Number of male adults (15-65 yrs)	1.68	1.24	0	9
Number of female adults (15-65 yrs)	1.74	1.31	0	21
Number of male elders (above 66 yrs)	0.24	0.46	0	2
Number of female elders (above 66 yrs)	0.12	0.35	0	3
Number of male children (0-14 yrs)	1.62	1.52	0	10
Number of female children (0-14 yrs)	1.58	1.47	0	10
Agricultural land owned (hectares)	4.97	14.21	0	612
Livestock owned (TLU)	4.01	9.88	0	298
Household has own business (1 yes)	0.46	0.50	0	1
Age of household head (years)	45.48	14.67	14	111
Female headed household (1 female)	0.13	0.34	0	1
Education household head (years)	3.96	4.13	0	18
Household has wage income (1 yes)	0.53	0.50	0	1
Financial assets (USD PPP)	778	3 734	0	166 666
Hh head born in village (1 yes)	0.55	0.50	0	1
Hh head belongs to largest ethnic group (1 yes)	0.66	0.48	0	1
Distance village center (minutes walking)	0.41	0.57	0	4
Distance forest (minutes walking)	0.59	0.79	0	5
Village level variables				
Village mean precipitation (1981-2010)	1 170	260	658	2 140
Village mean temperature (1981-2010)	23.39	4.13	13	29
Electrification (share of hhs with electricity)	0.05	0.17	0	1
Village market integration (mean cash/total inc.)	0.15	0.06	0.03	0.36
Country level variable				
GDP per capita (2010 USD)	739	532	344	2 311

Table A 7: Summary statistics of incomes: absolute and relative values

	Latin America	South Asia	East Asia	Africa	Global
Absolute income (AEU PPP USD)					
Total	4 850	1 459	1 675	1 015	1 642
Crop	831	373	422	379	438
Livestock	407	230	308	106	195
Environmental income	1 460	218	400	294	436
From forested areas	1 347	179	332	172	337
From non-forested areas	114	39	68	122	99
Plantation	1	34	14	17	17
Household	368	123	200	110	158
Wage	1 394	208	246	68	274
Other	390	273	85	41	124
Income shares[a]					
Crop	0.21	0.27	0.28	0.35	0.31
Livestock	0.10	0.13	0.16	0.12	0.13
Environmental income	0.31	0.18	0.26	0.29	0.27
From forested areas	0.28	0.15	0.21	0.19	0.20
From non-forested areas	0.03	0.03	0.05	0.10	0.07
Plantation	0.00	0.02	0.01	0.01	0.01
Household business	0.05	0.05	0.07	0.08	0.07
Wage	0.26	0.20	0.15	0.09	0.14
Other	0.08	0.14	0.06	0.05	0.07
N	848	1094	1297	4090	7329

[a] Mean shares are calculated by taking the mean of household shares.

7.3 Predicted income

Table A 8: Regression results (dependent variable: log of total income)

	Latin America	South Asia	East Asia	Africa
# of male adults (15-65 yrs)	0.0559**	0.0697***	0.1025***	0.0453***
	(0.0226)	(0.0223)	(0.0260)	(0.0120)
# of female adults (15-65 yrs)	0.0761***	0.1053***	0.0756***	0.0536***
	(0.0251)	(0.0233)	(0.0239)	(0.0119)
# of male elders (above 66 yrs)	-0.0948	-0.1188***	-0.0136	0.0148
	(0.0622)	(0.0356)	(0.0569)	(0.0298)
# of female elders (above 66 yrs)	-0.0951	-0.0967	0.0203	-0.0026
	(0.0797)	(0.0611)	(0.0777)	(0.0344)
# of male children(0-14 yrs)	0.0247	0.0240	0.0190	0.0316***
	(0.0198)	(0.0159)	(0.0289)	(0.0072)
# of female children (0-14 yrs)	-0.0139	0.0309	-0.0024	0.0344***
	(0.0147)	(0.0189)	(0.0190)	(0.0089)
Ag. land owned, ha (log)	0.0255***	0.0242***	0.0132	0.0131
	(0.0087)	(0.0085)	(0.0086)	(0.0106)
Livestock owned, in TLU (log)	0.0161**	0.0440***	0.0302***	0.0562***
	(0.0070)	(0.0093)	(0.0087)	(0.0060)
Hh business	0.2296***	0.0530	0.3756***	0.1836***
	(0.0513)	(0.0390)	(0.0688)	(0.0282)
Age of hh head (years)	0.0129	-0.0100*	0.0201*	0.0001
	(0.0096)	(0.0057)	(0.0103)	(0.0045)
Squared age of hh head (years)	-0.0001	0.0001**	-0.0002**	-0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0000)
Female headed hh (1 female)	-0.1201	-0.0618	-0.1934***	-0.2158***
	(0.0758)	(0.0535)	(0.0650)	(0.0331)
Education hh head (years)	0.0235***	0.0120**	0.0092	0.0083**
	(0.0071)	(0.0049)	(0.0068)	(0.0039)
Wage income (0-1)	0.1894**	-0.1607***	0.2623***	0.0458*
	(0.0773)	(0.0403)	(0.0665)	(0.0271)
Financial assets, in USD (log)	0.0909***	0.0513***	0.0624***	0.1181***
	(0.0162)	(0.0102)	(0.0141)	(0.0104)
Hh head born in village (1 yes)	0.0130	0.1141**	-0.0566	-0.0004
	(0.0577)	(0.0491)	(0.0745)	(0.0308)
Largest ethnic group (0-1)	-0.0128	0.0935*	-0.0464	0.0103
	(0.0554)	(0.0568)	(0.0592)	(0.0308)
Distance village center (hrs walk)	0.0663*	0.0402	-0.0409	-0.0060
	(0.0354)	(0.0345)	(0.1615)	(0.0300)
Distance forest (hrs walking)	0.0052	-0.1209***	-0.0702	-0.0355*
	(0.0261)	(0.0419)	(0.0935)	(0.0212)
Precipitation (1981-2010)	-0.0002	0.0004	0.0005***	0.0006
	(0.0002)	(0.0004)	(0.0001)	(0.0005)
Temperature (1981-2010)	-0.0041	0.0217	0.3217*	-0.0259
	(0.0354)	(0.0181)	(0.1797)	(0.0240)
Electrification	0.2315*	0.0318	-0.1995	0.1167
	(0.1247)	(0.1239)	(0.2413)	(0.1366)
Market integration	1.4602***	0.2958	1.0284	0.7601
	(0.4109)	(0.8539)	(1.0377)	(0.8215)
country==Belize	1.1229***			
	(0.3723)			
country==Bolivia	0.6734**			
	(0.3343)			
country==Brazil	0.3691			

	(0.3699)			
country==Peru	0.3158			
	(0.3474)			
country==Guatemala	0.3370*			
	(0.1803)			
country==Bangladesh		0.0200		
		(0.6387)		
country==Nepal		0.8104***		
		(0.1271)		
country==Cambodia			0.0209	
			(0.2250)	
country==China			3.3514**	
			(1.3620)	
country==Vietnam			1.6529***	
			(0.4717)	
country==Burkina Faso				0.4307**
				(0.1835)
country==Cameroon				0.3731*
				(0.2243)
country==Congo, Dem. Rep.				-0.3417**
				(0.1635)
country==Ethiopia				0.1160
				(0.2504)
country==Ghana				1.0726***
				(0.1286)
country==Malawi				-0.2845**
				(0.1393)
country==Nigeria				0.5532
				(0.4675)
country==Senegal				0.8185***
				(0.2773)
country==Uganda				0.4695***
				(0.1055)
country==Zambia				0.3824*
				(0.2001)
Constant	7.1686***	6.2474***	-3.0137	6.2999***
	(0.5000)	(0.8744)	(4.7898)	(0.6739)
N	848	1,094	1,297	4,090
R-square (overall)	0.49	0.43	0.33	0.52

* $p<0.1$; ** $p<0.05$; *** $p<0.01$.
Std.errors (in parenthesis) are clustered at village level.
Country dummies left out: Latin America - Ecuador, South Asia - India, East Asia - Indonesia, Africa – Mozambique.

7.4 Assets across household categories

Table A 9: Comparison of assets across household categories (global sample)

	Income & asset poor	*Income rich & asset poor*	*Income poor & asset rich*	*Income & asset rich*	Test statistics[a]
Productive assets					
Household size (AEU)	4.42	4.23	3.90	3.68	F=76.16***
Ag. land owned per AEU (ha)	0.82	1.08	1.29	1.87	F=51.10***
Livestock owned (TLU per AEU)	0.62	1.12	1.24	1.57	F=21.44***
Hh business (0-1)	0.26	0.28	0.43	0.48	χ^2=229.89***
Human capital assets					
Age of hh head (years)	46.4	46.3	45.3	44.9	F=5.54***
Education hh head (years)	3.14	3.22	4.19	5.29	F=159.71***
Female headed hh (0-1)	0.13	0.15	0.12	0.09	χ^2=11.79*
Wage income (0-1)	0.64	0.58	0.59	0.59	NS
Financial assets					
Financial assets per AEU (PPP USD)	118	196	549	953	F=78.13***
N	2863	801	801	2864	

*, **, *** Significantly different at 0.1, 0.05 and 0.01 level, NS=Not significant. [a] One-way ANOVA for continuous variables and Kruskal-Wallis for binary variables.