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Shock Waves: Managing the Impacts of Climate Change on Poverty

Background Paper

Responses to Weather and Climate

A Cross-Section Analysis of Rural Incomes

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Abstract

How much do poor rural households rely on environmental extraction from natural ecosystems? And how does climate variability impact their livelihoods? This paper sheds light on these two questions with household income data from the Poverty and Environment Network pantropical data set, combined with climate data for the past three decades. The study finds that extraction of wild resources (from natural forests, bushlands, fallows, etc.) provides on average as much income (about 27 percent) as crops across the smallholder sample. The cross-section data on past reactions to household self-perceived economic shocks and observed production reactions to climate anomalies can, respectively, provide hints about livelihood vulnerability to current climate variability, which is likely to worsen with climate change. Forest extraction did not figure among the most favored response strategies to households' self-perceived economic shocks, but households undertake subtle substitutions in sector production in response to weather anomalies that accentuate suboptimal climatic conditions for cropping. By relying more on forest extraction and wages, households compensate quite successfully for declining crop incomes. This paints a cautiously optimistic picture about fairly flexible rural livelihood reactions to current climate variability, and featuring forests as potentially important in household coping strategies.

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Responses to Weather and Climate: A Cross-Section Analysis of Rural Incomes

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Content

1 Introduction

Climate fluctuations and climate change can pose major threats to poor rural livelihoods in developing countries, affecting people in a variety of ways. Ecosystems may be permanently altered, with systemic impacts such as changed water availability. Fluctuations may become more frequent and extreme; weather events such as heavy rains, storms or droughts would become accentuated causing degradation effects such as accelerated soil erosion. In general, climatic variability may increase. Seasonal variations may become more unpredictable, and affect harvesting cycles. In production terms, both agricultural and forest-based production systems will be affected, depending on their site-specific capacity to adapt to the new conditions.

In many cases, the adaptation to changing climates and increased climate variability will predictably impose high costs on rural populations that depend largely on ecosystem services. The poorest segments of society will likely be particularly exposed, to the extent that they depend disproportionally on natural resources. Ecosystems play a key role in the livelihoods of the rural poor through: (i) agricultural incomes from activities that require intensive ecosystem management (cropping, livestock, or planted trees) and (ii) environmental incomes from the extraction of non-cultivated ecosystem goods, such as timber, plants and animals. Hence, the rural poor may depend crucially on ecosystem services, and thus be relatively more exposed to environmental degradation. This exposure to fluctuations in the supply of nature's goods and services could eventually also put at risk the attainment of various Sustainable Development Goals (SDGs).[2] Yet, so far there is little quantitative assessment of climate variability and its wider-reaching impacts.

Why is it thus interesting to look at environmental incomes in a climate change and poverty perspective? First, for specific mitigation activities such as the Reducing Emissions from Deforestation and forest Degradation (REDD/REDD+) efforts, the value of current forest uses could help us to quantify the opportunity costs of conservation and sustainable forest uses.[3] Second, income quantifications may help us understand the scope of coping with and adapting to climate change. The detailed assessment of household incomes can give us a benchmark for what income flows from crops, livestock, and the environment are at stake in various regions with differential exposure to climate risks. Finally, data on households' stated responses to different shock types and degrees can inform projections of responses to climate-induced fluctuations and shocks in different natural resource-based sectors.

This report will not deal with the opportunity costs of REDD, but address the two other issues through two research questions (RQ) on linkages between climate variability and rural livelihoods in developing countries. After initially presenting our conceptual framework and hypotheses (Section 2), we discuss our data sources for livelihoods and climate, respectively (Section 3). Using a big data set (8,000+ households) on rural livelihoods in tropical and subtropical areas, we provide a snapshot of assets, income generation and environmental reliance, and juxtapose those to climate zones and weather variables. In Section 4, we will address the first research question:

RQ1: How much do the rural poor depend on environmental incomes?

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[2] Among the 17 proposed SDGs, the most obvious links are to the ones on poverty, food security, health, water (1,2,3,6), the health of ecosystems (13-15), but more indirectly also goals related to e.g. employment (8), equality (10) or conflicts (16) could be affected (see https://sustainabledevelopment.un.org/sdgsproposal).
[3] This is not a topic we will cover in this report.

Our one-year income snapshot provides a static picture of the households' economic status. While this fails to capture explicit mechanisms of poverty dynamics (e.g. Hulme & Shepherd 2003), asset holding and other household characteristics may offer clues regarding whether households' poverty status is likely to be structural or stochastic (Carter & May 2001). A second, complementary report to the World Bank, drawing on the same household income data set, looks specifically at climate vulnerability from this angle (Dokken and Angelsen 2015). Instead, we will here describe the importance of environmental sources in rural household incomes. From scattered case study work done across the developing world over the last couple of decades, there are reasons to believe that environmental incomes occupy an important place in the household economy of many rural smallholders, especially as compared to official household surveys and national accounts, where these income sources tend to be heavily under-appreciated (Cavendish 2000; Vedeld et al. 2004). Vedeld et al (2004) in particular looked in their meta-study at 54 case studies where environmental income contributions had been quantified, and found an average environmental income share of 22%. The authors, however, also make various caveats about methodological inconsistencies within and between these studies, as well case selection biases that may have prevailed. These factors may make the calculated case average less representative of the rural developing world. The primary data presented below, gathered quarterly with a consistent methodology for household income accounting, should thus be able to consolidate that picture.

In Section 5, we will turn our attention to the second research question:

> *RQ2: How does climate variability affect the vulnerability of the rural poor through impacts on environmental and other incomes?*

We start by looking at household self-reported shocks, and responses to those, analyzing what household and contextual characteristics mattered in their decision whether or not to use environmental extraction as their principal coping response to the shock. We continue with an econometric analysis of how climate variability in our cross-sectional data may affect income levels and sector income composition. Previous studies have shown that agricultural income is particularly sensitive to changes in average temperatures and precipitation (Mendelsohn et al. 1994; 2007; Kurukulasuriya et al. 2006) and also to temperature and precipitation fluctuations (Deschênes & Greenstone, 2007). We combine these two strands of literature to ask how changing climate and variable degrees of climate shocks and anomalies likely affect rural household incomes from agriculture, the environment, and from other sectors, respectively.

In Section 6, we conclude by outlining our main findings, and discussing their scope. Notably, we will reflect on some important limitations in the extent to which we can reasonably interpret our cross-sectional results for a prediction of how climate change will affect rural production systems and livelihoods over time. On the other hand, as long as still no comprehensive time series data exist for how a changing climate affects the contribution of different sectors to livelihoods in developing countries, the cross-sectional multi-country pattern analyzed here can at least serve to refine our hypotheses regarding what impacts we may expect.

2 Conceptual Model

2.1 Key terms

We distinguish in the following between a series of key terms. First, “climate” is a longer-term measure for levels, variability and trends in temperature and precipitation. “Weather” we use to denote the shorter-term actually realized climatic levels, which thus includes a random element. While climate has many dimensions, below we will concentrate on the two main climatic variables that we could obtain long-term data for: temperature and precipitation.

“Climate variability” is probably the most overarching dynamic concept, referring 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). “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 change thus refers to a momentous alteration – typically observed for at least 30 years – in the mean, standard deviation and occurrence of extremes of climate parameters, e.g. precipitation, humidity, temperature, and wind. In this paper, we will due to data limitations not be able to test for increases in the standard deviation of weather variables – as mentioned above, this being one of the pathways through which climate change is expected to manifest itself – but rather focus on changing means, where relevant, and on weather anomalies.

The term “anomaly” we use for shorter-term, non-systematic variations in the same variables and indicators. In our empirical analysis, we define anomalies as normalized annual deviations from the long-term mean (z-values).

In behavioral terms, we assume rural households observe longer-term changes in climate, and allocate production factors (labor, land, capital) based on “expected weather”. For instance, climate means and weather anomalies are both used to test the response of agricultural incomes to climate variability, and to make predictions about climate change (Dell et al. 2014), but the interpretation of results differs between the two. While the rural households ex ante <u>adapt</u> their income strategies to long-run climate means, by definition they cannot similarly adapt to climate anomalies: they instead have to ex post <u>cope</u> with realized weather.

It is generally believed that optimal temperature and precipitation levels for economic activity exist (Park & Heal, 2014; Mendelsohn et al. 1994 specifically for agriculture). Economic activity is thus neither monotonously increasing nor decreasing in temperature and precipitation. This is especially true for activities relying on the productivity of living organisms. Agriculture is neither very productive in very hot sites nor in very cold climates, while the same is true for very wet or very dry conditions. From this observation follows that weather anomalies can have either positive or negative production impacts. For example, an above-normal rainfall can be beneficial for agriculture in dry climates but harmful for agriculture in humid climates. Likewise, an unusual warm year can be beneficial in cool climates but harmful for economic activities in warm climates. Whether a climate anomaly has a positive or negative production impact depends on if it takes weather conditions closer to or further away from their global optimum. We show these relations more formally below.

A diversified cropping strategy may reduce agricultural production risk caused by weather fluctuations (di Falco & Chavas 2008; 2009), both because of risk spreading on different crops, but sometimes also because of higher ecological resilience of diverse, assimilated farming systems, e.g. home gardens and agroforestry systems. Natural tropical forests, in turn, are among the most diverse ecosystems in the world, and have long-term evolved as functional ecological systems (MEA, 2005). As long as climate change does not pass certain critical thresholds, production systems based on extraction from natural ecosystems should thus on average be more resilient than crop production, at least if these natural ecosystems have not previously been heavily degraded (Locatelli *et al.* 2008). Environmental income streams may over time thus also be more stable than agricultural incomes, so that the former might have a buffering function for rural households.

Another reason why natural ecosystems can serve as an insurance mechanism against weather-induced income shocks is that they accumulate biomass. Many income-generating activities in natural ecosystems are based on the extraction of accumulated biomass such as firewood collection, timber production or fishing. Environmental shocks are normally affecting incremental biomass growth more than its accumulated stocks (e.g. Reed, 1979 & Clark, 1990, Nøstbakken & Conrad 2007). In contrast, crop production uses a large share of annually grown biomass. Even fruits from orchards originate from annual biomass production, and not biomass that accumulated over the years. Income from natural ecosystem is therefore less affected by weather shocks than agriculture as growth shocks in natural ecosystems level out over the years, smoothing natural incomes.

On the other hand, natural ecosystems are also far from immune to climate change effects. Disturbances such as droughts, wildfires, hurricanes, flooding, plant diseases and insect attacks can all also diminish the returns to forest-extractive activities, if they occur more frequently due to climate change. If changes in seasonal patterns occur, biodiversity could be affected. Fragility seems to be especially high in mountainous forests such as cloud forests, which usually from the outset display relatively high biodiversity levels per area unit. Forest management techniques may also have to be modified for forests to adapt successfully (Spittlehouse & Stewart 2004).

Not all climate change impacts on forests and plant growth will be negative. For instance, increases in atmospheric CO_2 levels can, if combined with sufficient access to water and nutrients, lead to a fertilization effect. Tropical forests have become long-term carbon sinks; they have been able to absorb larger amounts of carbon – to the extent of offsetting the carbon losses from tropical deforestation. While large uncertainties remain, recent research suggests that up to 60% of the current terrestrial carbon sink function could be caused by increasing atmospheric CO_2 (Schimel et al. 2015).

However, various climate models have predicted that especially the Amazon forests could be getting so dry that it passes a tipping point where large-scale forest die back will occur, driving a “savannization” process (Nepstad et al. 2008). In recent decades, several El Niño-induced droughts have increased the frequency of fires in tropical forests (Locatelli *et al.* 2008). The Amazon has indeed been getting drier since the 1970s, and recent research confirms that, while the Amazon forest still functions as a long-term net carbon sink, that function is declining continuously over time (Brienen et al. 2015).

In short, we have good reason to expect that the overall productivity of tropical forests to create extractive incomes for rural households is negatively affected by climate change and/ or greater weather fluctuations, but we should also expect to see that this productivity decline is inferior to the decline for agriculture (Locatelli et al. 2008). There are, nevertheless, large regional variations in both predicted change in rainfall and temperature, and in dry forest areas an increase in rainfall can be expected to have positive impacts on forest productivity.

Finally, forest conservation can create positive production externalities for other sectors, by helping preserve ecosystem services (such as watershed protection) that assist other sectors, including agriculture to adapt better to climate change.

2.2 Framework

In line with these deliberations, consider a rural household in a developing country with the following income sources: agriculture (with the subsectors cropping and animal husbandry), resource extraction (from natural forests as well as non-forest wildlands – bushlands, rivers, etc.), and incomes based on non-living assets (with the subcategories wage labor and other incomes). By definition, **"**total income" is the sum of agricultural, environmental, and other, non-resource incomes. We assume now that the village or site of the household's residence is hit by a climate shock.

As we discussed above, production based on biomass stocks may be less susceptible to weather shocks than production depending essentially on annual biomass growth. We therefore expect livestock husbandry to be less susceptible to negative weather shocks than crop production, and it may hence to a certain extent act as a buffer stock (e.g. Rosenzweig & Wolpin, 1993).

A corresponding distinction exists for extractive activities. Close to three fifths of extraction from forests comes from wood products (firewood, charcoal, timber, poles, etc.) (Angelsen et al. 2014). The stock of wood in a forest can thus be seen as an inter-annual portfolio where regrowth fluctuations may average out over the years till the trees are harvested. Conversely, extraction from non-forest environments is for half of its value dominated by foodstuff, especially from plant sources (Angelsen et al. 2014). We would thus also expect non-forest environmental extraction on average to be more dominated by annual biomass production, and thus more affected by weather anomalies than is forest extraction.

Biodiversity stabilizes biomass-based production (e.g. Hooper et al., 2005). As natural ecosystems are more diverse than agricultural systems, we assume that forest and non-forest environmental incomes are less affected by weather shocks than agriculture income.

Non-resource incomes, i.e. coming from outside the agricultural or forest/environmental sphere, could either be more or less affected by weather than agriculture (crop and livestock) and ecosystem services (forest and non-forest environmental income). We singled out wage incomes for particular inspection here, because wage employment was identified for the same data set as an important safety net (Wunder et al. 2014). Yet, in cases where most wage work is in agriculture, we would expect multiplier effects to be at work that eventually expose this sector more. Conversely, if wages come mainly from urban employment, the marginal productivity of labor in these sectors should be less affected by weather fluctuations, as compared to agriculture and forestry. Similar arguments can be made for other incomes like returns from businesses: the effect will depend on the type of business, and its backward or forward linkages to the resource sectors. We are thus ambiguous in our expectations to the relative climate sensitivity of non-resource incomes.

To further simplify the theoretical framework, we focus only on the labor allocation tradeoff, and assume that incomes are monotonously increasing in labor, but with diminishing returns.[4] The household's problem is to maximize expected utility from consumption by allocating labor to environmental, agricultural and other production, according to its weather expectations and weather realizations.

The problem of the household is to allocate labor across the sectors in order to maximize utility, taking the marginal productivity of labor as well as the correlation of production into account. For example, a

[4] Another possibility to the concavity assumption in production is that the household is risk averse, i.e. a concavity assumption in utility. With the concavity assumption in production we do not need any assumption about risk aversion for our framework.

household may invest more in a low-productive sector in order to reduce income fluctuations if its production is negatively correlated with other income sources. If the household can reallocate labor after weather realization it will allocate labor from the most affected sectors towards the least affected sectors. For our thought experiment, it implies that the households withdraws labor from crop and environmental production and reallocates it to forest and livestock production, due to our biomass accumulation argument. It implies further that relatively more labor is withdrawn from crop production than non-forest environmental production and more labor is allocated to forest production than to livestock production because of the biodiversity argument. If more labor is allocated to wage work and other non-resource based production depends on the changes of labor productivity in these sectors. If more labor is allocated to forest extraction, forest income could potentially *increase*, in spite of also being negatively affected in its productivity by the weather event. This will happen if the labor reallocation effect outweighs the income fall due to the direct damages from weather effects on forests (e.g. lower forest fruit and mushroom production, or less game availability). The response of other income sources to a negative agricultural shock will depend on its weather sensitivity. However, any weather shock that affects labor productivity in any sector adversely reduces total income and make the household worse off, but the extent of welfare losses will depend on how well the household can compensate the income shock by labor reallocation.

How well households can compensate for climate-related income losses depends, *inter alia,* on the sensitivity of the natural ecosystem to the shock, the output elasticity of labor in environmental production, and its market integration. Households can better compensate income shortfalls from agriculture if the natural ecosystem is highly resilient, or if off-farm income options exist. The labor elasticity depends on the response of the natural ecosystem to increased extraction. Small or fragile ecosystems may soon become overexploited and entail small labor elasticities.

2.3 Hypotheses

From the conceptual framework above, as well as empirical results from other studies, we derive three specific hypotheses. First, from the case study literature, and specifically the quantitative results in the Vedeld et al. (2004) meta-study, we would expect that:

> ***H1:*** *Households derive an income share of at least one-fifth from environmental sources, and the share of the poorest households exceeds that average.*

For cautionary reasons, we are setting our expectations here slightly below the case-average of 22% found in Vedeld et al. (2004), given the methodological problems and possible selection biases involved. The testing of this hypothesis will obviously set the stage for the rest of the report, in terms of determining how important a weight environmental income will carry in household decision-making vis-à-vis climate related factors.

Second, in terms of adjustments in the composition of household income sources, we would expect that households use the environment for coping in times of important economic setbacks, including but not only from weather-induced, household-reported shocks:

> ***H2:*** *Households self-reporting to have been hit by an economic shock will as a safety net significantly increase their environmental extraction.*

If environmental extraction works as a safety net, we would expect that environmental income is increased to substitute for other income or asset losses, or to mobilize emergency cash (or in-kind) resources needed to deal with the exogenous shock (e.g. to pay for transport or buy medicines).

A negative weather anomaly is likely to hit crop cultivation in particular, but we have to take into account that it could also hurt other activities, e.g. through damages to forest resources or access to them, decline in agricultural employment and businesses, etc. (see above). Based on the reasoning above regarding the differential impact on sector income components according to the variable dependence on weather-exposed annual biomass production, we expect the following impacts on sector incomes:

> ***H3:*** *A weather anomaly that reduces crop income by a percentage Δ ($\Delta Y_{crop} < 0$) triggers the following relative adjustments in income components:*
>
> *(i)* *Crop and non-forest environmental incomes are affected more negatively by weather anomalies than forest and livestock incomes (biomass accumulation).*
>
> *(ii)* *Agricultural income from crop and livestock production is more negatively affected by weather anomalies than income from forest and non-forest environmental income (biodiversity).*
>
> *(iii)* *Increased production in forest and livestock sectors following weather shocks can partially offset the losses in crop and non-forest environmental incomes (labor reallocation).*

2.4 Empirical specification

In this subsection, we derive an estimation strategy from the assumptions above for the test of the propositions specifically under Hypothesis 3. Each household may grow a different crop portfolio, selected based on the accumulated weather experiences (and resulting expectations), capital constraints, technologies, and other economic and environmental factors. Although crops may respond only to temperature and precipitation events above or below certain thresholds (Schlenker & Roberts, 2009; Roberts et al. 2012), quantifying such thresholds is not feasible for our sample, as it includes more than 250 crop species (not including livestock). Other studies have shown that temperature and precipitation matter most in the growing and harvesting season, and thus used seasonal temperature and precipitation variables (Mendelsohn et al. 1994; Kurukulasuriya et al. 2006).

However, most of our sites are located in areas with more than one cropping season (Zabel et al. 2014). As the start and end of each cropping season depends on geographic location, with our villages located both north and south of the Equator, this approach becomes cumbersome to implement. We therefore use average annual temperatures and annual precipitation as the relevant climate variables. Several studies have shown that the response of crops to changing temperature and precipitation may be approximated by a quadratic function (Lobell et al. 2011; Burke & Emerick 2015). If the yield of each crop to weather can be approximated by a quadratic function, we can conclude that the yield of an aggregated crop portfolio can also be approximated by a quadratic function, for the common support of crops.[5] As we have no reason to

[5] The reason is that a linear combination of quadratic functions will also come to be a quadratic function. The same holds also true for the aggregation of crop portfolios in their common support. However, if some crops yield zero harvest for temperatures and precipitation levels in the range of interest, it would add some non-convexities to the household's harvest, with crop portfolios rather having bell-shaped responses to climate variables. We assume in the following that most crops yield strictly positive harvests in the climates of interest, such that crop yields can be approximated by a second-order polynomial. We are not interested in the crop yields, but we use profits to aggregate yields of a crop portfolio. The profits from crop portfolios can also be approximated by a quadratic function if they

assume a specific functional form for environmental income, other or total income, we use a quadratic function, which may be justified by a second-order Taylor approximation.

In the previous section we had argued that households respond in two ways to climate and weather, respectively. In a first step, they choose income activities and crop portfolios according to their climate-based weather expectations. In a second step, they redirect some production factors after weather realization. We measure the former impact on income by including *climate means* in our regression framework. To account for the latter effect we include as weather deviations from the mean in our survey year *weather anomalies*. The impact of a positive deviation from the mean temperature or precipitation on agriculture depends on the regional climate. We therefore allow the effect of a positive and a negative shock to differ between hot or wet and cool or dry climates (see Section 2), hence using interaction terms in the estimation part (Section 5).[6]

In this specification, the coefficients of the climate means capture the effect of expected weather on expected income. With caution, they can be interpreted as the effect of climate change with adaptation (Dell et al. 2014). The point estimates for the deviations from mean climates capture the effects of climate shocks on income. They can be interpreted as the effect of weather shocks on income with *ex post* coping but no *ex ante* adaptation. The coefficients on the interaction terms capture the effects that a deviation from the mean may have different effects on income, depending on the mean. For instance, more rain in humid climates likely means something different than more rain in dry climates.

Unlike some studies that analyzed the effect of floods on income (e.g. Bui et al. 2014) we have no problem with spatial endogeneity. Our weather anomalies are standardized by the standard deviation of weather in a specific location. Therefore they reflect an unusual large deviation of weather from the mean and all villages face similar probabilities of weather anomaly as a result.

Next, we want to address the question of which controls to include. Any controls that the household has at its command could potentially bias the climate results, as they can be employed according to weather expectations or realizations, and may thus themselves be functions of weather (Welch et al. 2010). Further, to the extent that income is a function of climate, and capital is related to accumulated income, then capital will be a function of climate as well. Including capital endowments might therefore potentially pick up a large share of the climate effect on sector income. On the other hand, households' accumulated assets (including human capital) are co-determined by many factors that are independent of climate, and have thus also in our previous analyses proved to be important contextual factors in explaining household income differences in the PEN data (Angelsen et al. 2014). Furthermore, comparing estimations both with and without capital/asset controls may allow us to distinguish some *ex ante* adaptive strategies of

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are an affine transformation of the crop yields. This is because the affine transformation of a quadratic function is quadratic function. This result allows for a wide range of profit specifications involving fixed and proportional costs.

[6] If the response of income to weather can be approximated by a quadratic function of mean annual temperature (temp) and total annual precipitation (prec), then this is equivalent to regressing income on climate means in linear and squared from, deviation from the climate means in linear and squared form, and the linear interaction terms between climate means and deviation from the climate means. We drop the squared terms for the temperature and precipitation anomalies, as few values exceed unity and the differences between the linear and squared term are small).

households in response to climate change. By including capital stocks into the regression framework, we can further ask how investment affects vulnerability to climate means and anomalies.

For our empirical strategy, we regress the income of household i in village j and sector k on weather anomalies ($weather_j$) climate variables ($climate_j$) in village j and village-level controls (X_j) such as regional dummies, infrastructure and soil attributes, estimating

(1) $income_{ijk} = \alpha + \beta\ weather_j + \gamma\ climate_j + \delta\ climate_j^2 + \eta\ weather_j \times\ climate_j + \rho\ X_j + \varepsilon\_ijk.$

The coefficients of interest are β, γ, δ and η, measuring the impact of climate means and weather anomalies on sector-wise incomes. Weather anomalies are defined such that they can be positive and negative. A positive coefficient for precipitation anomalies means that more rain increases income. However, the marginal effect of a weather anomaly is given by the sum of the linear and the interaction term. A positive coefficient for a weather anomaly in linear form and a negative coefficient in interacted form mean that more precipitation or temperature is only good in dry or cold areas while detrimental to production in humid or warm areas.

Annual income is given in 2005 USD ppp. We transform incomes by inverse hyperbolic sine transformation (Burbidge et al., 1988) to reduce the weight of outliers and to acknowledge the fact that some incomes are zero. The interpretation as percentage changes is maintained with inverse hyperbolic sine transformations.

To account for the clustering of households in villages, and that some variables are observed at the village and not household level, we cluster standard errors at the village level.

3 The Data

3.1 Poverty and Environment Network (PEN)

The income data used in this report draw on the global PEN database. PEN is a large data collection effort, which has been led by the Center for International Forestry Research (CIFOR) (http://www1.cifor.org/pen/). The effort was originally inspired by the influential case study done by Cavendish (2000), which documented a high household income share from environmental sources, i.e. extraction of natural resources from wildlands – that is, natural forests, grasslands, rivers, fallows, or other non-cultivated environments. Notably, Cavendish discovered this sizeable 'subsidy from nature' by applying detailed quarterly household surveys with shorter recall periods (1-3 months) and capturing seasonal variations. Furthermore, much of this 'hidden harvest' came in the form of subsistence income, making it necessary to impute prices that could measure this income contribution in value terms.

The starting point of PEN was the idea to answer that question by replicating an adapted and extended version of the Cavendish survey across developing countries in various continents, covering different contextual preconditions. This would then allow for a much more consolidated view about the role of environmental incomes in the tropics and subtropics. PEN thus used standard household and village survey instruments, translated into different languages, to provide new data, so as to analyze the two-way linkages between poverty and environmental incomes. 33 PhD students and other junior scholars were involved in data collection between 2005 and 2008, and supervised by a dozen of senior researchers. The data gathered eventually covered 24 countries, spread over Sub-Saharan Africa, South and East Asia, and Latin America. We have data for a total of 58 sites, 333 villages, and 7978 households (Angelsen et al. 2014).[7] The intention was thus to make PEN the world's largest global-comparative quantitative review of the role of tropical forests in poverty alleviation.

We use different sector incomes and total household income in our analysis. Incomes include cash and non-cash components, as calculated by Angelsen et al. (2014). The agricultural sector includes crop and livestock income, while the environmental sector includes incomes from natural forests, as well as other non-cultivated sources. Among non-resource sector incomes, we separate out wage income from other sources, dominated by business and transfer incomes (remittances, pensions, etc.). Total income aggregates agriculture, environment and non-resource incomes. Finally, we compute households' adult equivalent units (aeu) to enable adequate welfare comparisons across households with different compositions of productive earners vs. non-earners, and size-dependent economies of scale in the per-capita provision of intra-household services.[8]

3.2 Climate data and contextual variables

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 4000 individual

[7] The initial sample of 8 305 households was reduced by an attrition of 3.9%. In addition, the sample in multivariate analyses is further reduced by missing (or erratic) information on specific contextual variables (see below).
[8] OECD discusses different options for using equivalence scales (http://www.oecd.org/eco/growth/OECD-Note-EquivalenceScales.pdf).

weather station records (Harris et al. 2013). These data are commonly used in economic studies (Aufhammer et al., 2013; Dell et al. 2014).

We use annual means of precipitation and temperatures for the reference period from 1981 to 2010. We chose the last year of the reference period such that it equals the last year of fieldwork for the PEN study. The selected period length of 30 years is covered by most climatologies, and may be reasonably relevant for current household decision-making. The squared climate terms account for nonlinearities in the response of income to climate (Mendelsohn et al. 1994, 2007; Kurukulasuriya et al. 2006, and Section 2).

To obtain the temperature anomalies, we use the mean temperature of the survey year (temp_survey) minus the average temperature of the reference period (temp_mean) and divide the difference by the standard deviation of temperature in the reference period (temp_sd):

$$\text{temp\_anomaly} = \frac{\text{temp\_survey} - \text{temp\_mean}}{\text{temp\_sd}}.$$

The precipitation anomalies are calculated correspondingly. We define the survey year as the year that starts with the survey period, i.e. three months prior to the first interview round within a village.[9] The anomalies measure therefore deviations from the means in terms of standard deviations (e.g. Lobell et al. (2011).

The soil data are from the Harmonized World Soil Database v 1.2. The data on forest cover are based on MODIS-satellite based estimations of tree canopy cover (in percent) at 250 m spatial resolution globally (Hansen et al. 2010).[10]

For estimating the distance to the nearest city, we use ESRI's world cities shape file of the year 2008 that is available online (http://www.baruch.cuny.edu/geoportal/data/esri/esri_intl.htm). The distance was calculated as Euclidian spatial distance between each PEN village centre and the nearest city, expressed in km. Similarly for distance to major roads, we used the world data on major roads shape file available online (http://www.vdstech.com/world-data.aspx). The distance in km is referring to both secondary and primary roads in the datasets.

When the Köppen-Geiger climate classification, according to Peel et al. (2007), is superimposed on the location of the PEN sites, most of the PEN villages are located in the tropics, and subsidiarily in the subtropics, with just a few temperate sites complementing the picture. No PEN site is located in arid, cold or polar climates.

3.3 How representative and applicable are the PEN data?

As for the PEN data, what universe is the sample representative of? The sheer number of countries, sites, and villages does obviously not *per se* safeguard any wider scope of extrapolation, if the sample was not randomly selected, and if in the worst of cases the sample was subject to systematic selection biases. For addressing this concern, we thus first have to look closer at the PEN sampling strategy at multiple levels (Wunder et al. 2014). As a collaborative research effort with a relatively limited budget, PEN was not able to choose its study sites randomly, which were rather determined by the sites PhD students had preselected.

[9] It starts three month before the first interview round since the households were asked about their incomes in the last three month.

[10] We are grateful to Martin Herold and his team at Wageningen University for providing to us these data for the PEN villages.

However, one research grant allowed us to fill some geographical gaps, such as in West Africa and Southeast Asia. Overall, due to a special interest in forests, it was a precondition that some forest cover was still present; on the other hand, very remote indigenous hunting and gatherer cases with close to 100% forest cover were also omitted as too special scenarios. In addition, Africa is as a continent somewhat oversampled in PEN (slightly over half of the households). Within the study sites, the selection of villages was stratified so as to capture variation across some predefined (and partially correlated) gradients: remote vs. market-near areas, rich vs. poor in forest resources, indigenous vs. mixed populations, high vs. low population density, etc. Within villages, households were invariably selected by random sampling from (pre-existing or newly implemented) village census lists.

Second, after having collected the data, we also empirically tested for biases in the global PEN sample vis-à-vis the rural tropics with respect to two key variables: forest cover and population density were compared to province- and village-level developing-country controls (Angelsen et al. 2014: Annex). The PEN study areas match the full forest-cover range of controls, but somewhat overweight high forest-cover cases. Likewise, PEN does not cover cases with very high rural population density. Finally, it also excluded corporate forest frontiers dominated by largeholders. Hence, we can comfortably say that PEN is probably adequately representative of smallholder-dominated tropical and sub-tropical rural landscapes with moderate-to-good access to forest resources, and all but very high population densities. This implies that results should be trustworthy for the bulk of rural developing country settings, though they could differ for some of the under-represented locations.

A second concern is relevant when we bring in the climate: we are looking at the adaptive capacity of households through the lens of a cross-section. Our PEN sample includes rural households in 20 countries, with tropical as well as subtropical areas. While we have annual income and its disaggregation on four quarters, we do not have time series data, or at least several points of observation, to study households' adaptation strategies in a longer perspective. We are thus estimating how households currently adapt their productive systems along a gradient of climate variables (temperature, precipitation, and their respective anomalies), within specific asset levels and contexts (at the country, village and household levels). We will below analyze these cross-sectional patterns from the angle of climate *variability*, but will deliberately not refer to climate *change*. We still hope that some of our conclusions can be given a time-relevant interpretation, and will in the closing section discuss under which circumstances and to what extent such an interpretation of the identified climate gradients may be adequate.

4 Estimating Environmental Income of the Rural Poor: A Snapshot

4.1 Overall income

Table 1 summarizes for all households surveyed in the PEN study our results regarding total household income, its cash portion, and its sector origin: crops, livestock, forest and non-forest environmental incomes, wages and other incomes. Forest environmental incomes include all non-cultivated sources such as, for instance, timber and firewood from natural forests, wild fruits and vegetables from grasslands, as well as non-farmed fish. Forest incomes include all environmental incomes that originate from the forest;[11] non-forest environmental income denominates the residual from all other non-cultivated sources. Finally, agricultural incomes include incomes from all types of livestock and crop cultivation. The reported incomes represent gross incomes minus variable costs, including purchased labor costs. However, capital depreciation and family labor were not deducted (Angelsen et al. 2014).

Table 1: Annual household incomes in the PEN sites. PPP converted 2005 US$ adult equivalent units (aeu)

	Latin America & Caribbean	South Asia	East Asia & Pacific	Sub-Saharan Africa	PEN total
Total income [US$ pc/year]	4549	1449	1663	1019	1692
Total cash income [US$ pc/year]	3558	919	1224	615	1181
Share cash in total income [%]	78	63	74	60	70
Crop income [US$ pc/year]	754	372	415	371	434
Crop cash income [US$ pc/year]	498	132	221	180	226
Share of crop income in total income [%]	17	26	25	36	26
Share of crop cash income in crop income [%]	66	35	53	48	52
Livestock income [US$ pc/year]	438	214	281	104	197
Livestock cash income [US$ pc/year]	355	112	224	67	141
Share livestock income in total income [%]	10	15	17	10	12
Share cash in livestock income [%]	81	52	80	65	72
Forest income [US$ pc/year]	1217	175	311	158	338
Forest cash income [US$ pc/year]	711	36	186	82	183
Share forest income in total income [%]	27	12	19	16	20
Share cash in forest income [%]	58	21	60	52	54
Environmental income (non-forest) [US$ pc/year]	174	40	77	131	116
Environmental cash income [US$ pc/year]	40	5	24	42	34
Share non-forest environmental income in total income [%]	4	3	5	13	7
Share cash in non-forest environmental income [%]	23	13	31	32	29
Wage income [US$ pc/year]	1183	207	243	71	278
Share wage income in total income [%]	26	14	15	7	16
Household size	6	5	5	7	6
Number of households	1140	1114	1348	4376	7978

[11] We have abstracted here from the small share of forest income (global average around 5%) that comes from forest plantations, and thus is not of environmental origin.

More than two-thirds of total income (70%) in the PEN sample is cash; the remainder is subsistence income. Agriculture (crops and livestock) is with an income share of 37% the single most important income source. Environmental income follows with 27% of the total income – more or less equal in size to the cropping part of agriculture (26%). Three fourths of the environmental income comes from forests. Both absolute and relative incomes vary strongly across regions. Latin America has the highest absolute incomes, Sub-Sahara Africa the lowest, and both exhibit a high standard variation. The two Asian regions lie in between, but are closer in their average to Africa than the high-income Latin American sites.

As we would have expected, the share of cash income is positively related with total income, while the share of crop income follows the opposite pattern. There is no uniform relation between environmental income and total income at this aggregated scale.[12] Environmental income (forest and non-forest combined) is the lowest in South Asia (12% forest, 3% non-forest environmental income), probably because population density is high and fewer wildlands and quality natural resources are left to provide environmental supplies to households. The share of environmental and forest incomes in Latin America and East Asia & Pacific, in turn, are upwards biased by some outlier sites of commercial high-value forest products, such as Brazil nuts, assai palm and bamboo. The cash share in forest incomes is thus also high in Latin America (58%) and in East Asia & Pacific (60%), while it is lowest in South Asia (21%) where forest incomes are dominated by firewood for domestic use. The regional shares thus also express some structural differences in what type and values of forest products are being harvested.

4.2 Environmental income among the poorest

Table 2 provides for comparison the same income measures as Table 1, but for the poorest of the poor, i.e. the lowest country-wise income quintile in our smallholder sample. A striking difference between the poorest fifth of the population and the total population is the lower market integration of the poor: only half of their incomes are cash incomes. Otherwise, income levels and shares of the poorest fifth follow the same regional pattern as incomes of the total population. In general, mean environmental, forest and agricultural incomes are slightly higher for the poorest fifth than for the total population. In South Asia, however, environmental income shares are much higher for the poorest income quintile, and agricultural income shares are correspondingly lower.

Table 2: Lowest income quintile: annual household incomes for the poorest quintile in the PEN sites. PPP converted 2005 USD adult equivalent units (aeu)

	Latin America & Caribbean	South Asia	East Asia & Pacific	Sub-Saharan Africa	PEN total
Total income [US$ pc/year]	896	505	374	178	230
Total cash income [US$ pc/year]	596	287	224	81	112
Share cash income in total income [%]	67	57	60	46	49
Crop income [US$ pc/year]	205	116	112	58	74
Crop cash income [US$ pc/year]	118	30	32	14	20
Share crop income in total income [%]	23	23	30	32	32
Cash share in crop income [%]	58	26	29	24	27
Livestock income [US$ pc/year]	80	40	41	18	25

[12] See also Angelsen et al. (2014): there is no clear relationship between average environmental (or forest) income shares and average total income at the site level (there are 58 sites in the PEN sample).

	Latin America & Caribbean	South Asia	East Asia & Pacific	Sub-Saharan Africa	PEN total
Livestock cash income [US$ pc/year]	45	18	25	12	15
Share livestock income in total income [%]	9	8	11	10	11
Cash share in livestock income [%]	56	46	62	67	61
Forest income [US$ pc/year]	198	107	64	32	42
Forest cash income [US$ pc/year]	81	19	35	8	12
Share forest income in total income [%]	22	21	17	18	18
Cash share in forest income [%]	41	18	54	24	29
Non-forest environmental income [US$ pc/year]	56	18	34	25	27
Non-forest environmental cash income [US$ pc/year]	5	2	8	3	4
Share non-forest environmental income in total income [%]	6	4	9	14	12
Cash share non-forest environmental income [%]	9	13	23	12	15
Wage income [US$ pc/year]	211	147	61	20	29
Share wage income in total income [%]	24	29	16	11	13
Household size	7	6	6	7	7
Number of households	228	223	270	875	1596

Table 3 now instead features the top-20 quintile. It should be remembered that only few of these households could genuinely be called "rich", even by their own developing country standards, since our rural smallholder sample by definition is focused on the poor. The results here mirror the ones from the poorest quintile, with the opposite sign: three fourths of all income is cash; wage income (by definition, cash-based) is unsurprisingly at 946 US$/pc/year more than thirty times higher than in the poorest quintile (29 US$/pc/year). Perhaps less expected is it that extractive incomes are also high in absolute terms for the top-quintile: non-forest environmental incomes are at 27 US$/pc/year for the lowest and 343 US$/pc/year for the top quintile; for forest incomes the quintile relationship is even more disparate (though again boosted by Latin America in particular): 43 US$/pc/year vs. 1111 US$/pc/year. There is thus no indication that extractive products would display a marked pattern of 'inferior products' that were to decline markedly in importance when turning to the upper income scales.

Table 3: Highest income quintile: annual household incomes for the top-20% income households in PEN sites. PPP converted 2005 USD adult equivalent units (aeu)

	Latin America & Caribbean	South Asia	East Asia & Pacific	Sub-Saharan Africa	PEN total
Total income [US$ pc/year]	12639	3184	4005	3166	5299
Total cash income [US$ pc/year]	10322	2221	3221	2085	4008
Cash share in total income [%]	82	70	80	66	76
Crop income [US$ pc/year]	1984	715	821	1182	1183
Crop cash income [US$ pc/year]	1417	302	500	670	722
Share crop income in total income [%]	16	22	21	37	22
Cash share in crop income [%]	71	42	61	57	61
Livestock income [US$ pc/year]	1171	586	777	263	582
Livestock cash income [US$ pc/year]	1058	338	649	192	464
Share livestock income in total income [%]	9	18	19	8	11
Cash share in livestock income [%]	90	58	84	73	80
Forest income [US$ pc/year]	3223	277	649	456	1111
Forest cash income [US$ pc/year]	1888	56	393	289	656
Share forest income in total income [%]	26	9	16	14	21

	Latin America & Caribbean	South Asia	East Asia & Pacific	Sub-Saharan Africa	PEN total
Cash share in forest income [%]	59	20	61	63	59
Non-forest environmental income [US$ pc/year]	379	60	113	462	343
Non-forest environmental cash income [US$ pc/year]	114	4	55	172	119
Share non-forest environmental income in total income [%]	3	2	3	15	6
Cash share of non-forest environmental income [%]	30	7	49	37	35
Wage income [US$ pc/year]	3622	219	570	175	946
Share wage income in total income [%]	29	7	14	6	18
Household size	4	5	4	6	5
Number of households	228	223	270	876	1596

For the sake of completeness, Table 4 also gives the income numbers for the three middle-income quintiles, i.e. the residual group after that the top 20% and the bottom 20% have been subtracted. Various values are unsurprisingly fairly similar to the average income values expressed in Table 1; however, there are exceptions. For instance, livestock, wage and even forest incomes are for those groups on average only close to half of the overall household average, indicating some tail-skewed distributions at the upper end: high-earning groups households raise the overall average well beyond the median, which will typically be located in this middle-rage group – more so than e.g. for crop income.

Table 4: Middle-income quintiles (20-80%): annual household incomes in PEN sites. PPP converted 2005 USD adult equivalent units (aeu)

	Latin America & Caribbean	South Asia	East Asia & Pacific	Sub-Saharan Africa	PEN total
Total income [US$ pc/year]	3070	1185	1310	583	977
Total cash income [US$ pc/year]	2290	694	891	302	594
Cash share in total income [%]	75	59	68	52	61
Crop income [US$ pc/year]	527	343	381	206	304
Crop cash income [US$ pc/year]	319	108	190	72	129
Share crop income in total income [%]	17	29	29	35	31
Cash share in crop income [%]	61	32	50	35	42
Livestock income [US$ pc/year]	313	148	196	79	126
Livestock cash income [US$ pc/year]	225	68	148	44	75
Share livestock income in total income [%]	10	12	15	14	13
Cash share in livestock income [%]	72	46	75	55	60
Forest income [US$ pc/year]	888	163	280	101	178
Forest cash income [US$ pc/year]	529	36	166	38	82
Share forest income in total income [%]	29	14	21	17	18
Cash share in forest income [%]	60	22	59	37	46
Non-forest environmental income [US$ pc/year]	145	41	79	57	69
Non-forest environmental cash income [US$ pc/year]	27	7	18	12	15
Share non-forest environmental income in total income [%]	5	3	6	10	7
Cash share in non-forest environmental income [%]	18	16	23	21	22
Wage income [US$ pc/year]	694	222	195	54	138
Share wage income in total income [%]	23	19	15	9	14
Household size	6	5	5	7	6
Number of households	684	668	808	2625	4786

The poorest 20% of households in an African setting thus command a substantially different set of material entitlements than their Latin American bottom-quintile counterparts. But in addition to relative poverty (Table 2), we may also be interested in measures for the absolute poorest, looking at the 27% of households living below the commonly used poverty line of 1.25 US$/aeu/day (Table 5). This puts more spotlight on a low-income region like Sub-Saharan Africa where 43% of households fall under this poverty line, while in Latin America only 2% do. Of the 2,169 households falling under this absolute poverty line, 88% are from Sub-Saharan Africa. The results for environmental dependence are similar to those for the lowest quintile groups: 29% for the absolutely poorest versus 30% for the lowest quintile. The continental differences we observe between the two are much due to the very restricted sample of households under the US$1.25 limit outside of Sub-Saharan Africa. This also suggests that the structural differences between regions are probably more important in explaining income composition than is the level of total household income.

Table 5: Household incomes below the US$1.25/person/day poverty line in PEN sites. PPP converted 2005 US$ adult equivalent units (aeu)

	Latin America & Caribbean	South Asia	East Asia & Pacific	Sub-Saharan Africa	PEN total
Total income [US$ pc/year]	334	353	278	272	276
Total cash income [US$ pc/year]	225	196	163	129	135
Cash share in total income [%]	67	56	59	48	49
Crop income [US$ pc/year]	95	74	81	92	90
Crop cash income [US$ pc/year]	57	16	20	25	25
Share crop income in total income [%]	28	21	29	34	33
Cash share in crop income [%]	60	22	24	28	28
Livestock income [US$ pc/year]	56	19	31	31	31
Livestock cash income [US$ pc/year]	40	10	19	18	18
Share livestock income in total income [%]	17	5	11	12	11
Cash share in livestock income [%]	71	53	61	56	57
Forest income [US$ pc/year]	26	90	41	50	51
Forest cash income [US$ pc/year]	5	10	18	15	15
Share forest income in total income [%]	8	25	15	18	18
Cash share in forest income [%]	21	11	44	31	30
Non-forest environmental income [US$ pc/year]	37	7	24	31	30
Non-forest environmental cash income [US$ pc/year]	3	0	6	5	5
Share non-forest environmental income in total income [%]	11	2	9	11	11
Cash share in non-forest environmental income [%]	9	0	24	15	15
Wage income [US$ pc/year]	42	122	54	30	35
Share wage income in total income [%]	13	35	19	11	13
Household size	9	6	6	7	7
Number of households	23	75	171	1900	2169

In Table 6, we look at the share of the population that falls below the poverty line, if we hypothetically subtracted subsistence income, forest income, or total environmental (forest plus non-forest) income, respectively, from total household income. This gives us an indication for what overall impact these sector incomes have on welfare and equity goals. As mentioned, just over one fourth of the PEN sample households fall below the poverty line, but if only cash income was included to calculate the poverty line, as much as half of the sample population would fail to climb above the poverty line. This strong effect can be explained by the fact that the poor have very high shares of subsistence incomes, especially in South

Asia. Similarly, if we did not record forest income (or all environmental incomes, respectively), a much larger share of the PEN sample households (36% for forest income, 41% for all environmental income excluded) would fall below the poverty line. Hence, we can say that for 14% of all households the access to (forest and non-forest) environmental resources makes an income difference that comes to lift them above the international poverty line (for forest incomes alone, the share is 9%). Correspondingly, income surveys such as the Living Standard Measurement Surveys (LSMS) that capture environmental incomes only superficially (if at all) will come to overestimate the degree of local poverty when people have access to rich extractive resources (Davis et al. 2010).

Table 6: Share of the population below the US$1.25 poverty line, for different income measures (%)

	Latin America & Caribbean	**South Asia**	**East Asia & Pacific**	**Sub-Saharan Africa**	**PEN total**
Total income	2	7	13	43	27
Cash income only	8	32	31	69	49
Total without forest income	6	14	22	54	36
Total without forest and non-forest environmental income	9	17	27	59	41

Lastly, we also compare inequality within regions, using different income aggregations (Table 7). For recall, the Gini coefficient expresses the share of total income mass that should be moved around in the income distribution to make all participants equal. As compared to the baseline Gini for the full sample, the coefficient rises sharply if we were to consider only cash income (i.e. excluding subsistence incomes), and for most continental regions to a lesser extent if we excluded environmental income (or alternatively only its forest component): the increment in the Gini coefficient is between 0.03 and 0.07, meaning that an additional 3-7% of income would have to be moved around to restore the same level of equality as was found in the full sample. This indicates the egalitarian effects of both subsistence income and forest/ environmental income. Note also that the Gini coefficients here are calculated for the full regional samples. When we consider income inequality at each site, the average Gini is somewhat lower: 0.35 for total income and 0.39 when environmental incomes are excluded (Angelsen et al. 2014).

Table 7: Income inequality for different income types; Gini coefficients

	Latin America & Caribbean	**South Asia**	**East Asia & Pacific**	**Sub-Saharan Africa**
Gini total income	0.50	0.37	0.44	0.57
Gini cash income only	0.55	0.46	0.52	0.66
Gini without forest income	0.55	0.40	0.48	0.60
Gini without environment income	0.57	0.41	0.50	0.60

In conclusion of this section, where do these results leave us with respect to our Hypothesis 1, stating that "*Households derive an income share of at least one-fifth from environmental sources, and the share of the poorest households exceeds that average*"? For the global sample average, the expectation about high environmental income levels was clearly fulfilled (Table 1): an income share of 20% was derived from forests alone, while adding non-forest environmental incomes brought the share up to 27% -- basically the same as for crops. For all regions the combined environmental income share exceeds 20% (Latin America 31%, East Asia & Pacific 24%, Sub-Saharan Africa 29%) – except for South Asia, where with 15% (12% forest, 3% non-forest) the share lags markedly behind.

What if we look at the poorest groups separately: did their environmental income share exceed the full-sample average? For the poorest quintile, the environmental income share is indeed with 30% some 3% points higher than for full sample, although this conceals a slightly lower forest income share (18%), and a much higher non-forest environmental income share (12%) that is important particularly in Africa (Table 2). Cropping here makes up 32% of income, compared to 26% in the full sample. If we look instead at the absolutely poorest (income under US$1.25 per capita/day), the picture is similar (Table 6): forest income is 18%, the non-forest environmental income share is 11%, making the combined share (29%) higher than for the full sample. Crops here contribute 33% of income. In other words, our answer regarding the alleged over-proportional reliance of the poor on the environment is certainly confirmative, although this is due to higher reliance on non-forest, rather than on forest extraction. Also, since the share of crop income is also generally higher among the poorest groups, it is reasonable to conclude that the poorest households are more natural resource dependent in general.

Noteworthy is also the high degree of income diversification that we find in all our four target regions. As we could see in Table 1, cropping income share varied in the 17-36% range across regions, livestock 10-17%, forest income 12-27%, non-forest environmental income 3-13%, and wages 7-26%. As observed elsewhere, such a high degree of income diversification is common for rural livelihood strategies in developing countries (e.g. Ellis 2000). Diversification can be a caused by pull factors (e.g. realization of complementarities between activities), but when caused by push factors it tends to come at the cost of foregone specialization on the most productive activities – often in anticipation of past risks, or *ex post* coping responses to shocks (Barrett et al. 2001; Dercon 2002). Climate variability is one of those risks faced by poor rural households, which we will thus deal with in the following section, analyzing to which extent the sector composition of income sources is sensitive to climate fluctuations.

5 Estimating the Effects of Climate Variability

5.1 Reported shocks and coping strategies

We now turn our attention to the second research question of his report, related to the impact of climate variability on income generation. We begin with an examination of household self-reported shocks in the PEN survey. We are scrutinizing now households' preferred coping strategies, with special attention to Hypothesis 2 suggesting safety net responses based on environmental extraction. The PEN survey included questions on household self-reported experiences of shocks, their severity and cause, and responses to cope with them. Here our interest lies in studying which household and village level characteristics are associated with the decision to extract additional products from forests and other natural environments, in response specifically to shocks that potentially are climate-related. We thus focus on the following shock types:

1. Serious crop failure
2. Major livestock loss
3. Other major asset loss

These categories will also come to cover some non-climate related shocks (such as theft or non-climate related pests), but presumably represent a subset with greater climate relevance than the total amount of shocks analyzed in Wunder et al. (2014). Households reporting a shock were also asked to rank their responses by importance. Responses included 21 predefined options, plus an open answer option. We categorize our response variable as 1 = "harvest more forest or wild products" and 0 = "any other action or non-action". Wunder et al. (2014) show that second and third rank responses exhibit a similar distribution across response categories. Here we thus only analyze the first ranked response.

Since not all surveyed households reported a shock, the sub-sample of households that did could potentially be biased. We address this by using a maximum likelihood Probit model with sample selection implemented, using the Stata command "heckprobit". The variables used in the regression analysis are reported in Table 8. Repeated observations (when households reported more than one shock) are weighted using frequency weights. Note that households also reported whether the shock was perceived as "severe" or "less severe".

Table 8: Self-reported characteristics of households experiencing shocks: descriptive statistics

	Unit	mean	SD	Min	Max
Used forest or wild products	yes/no	0.08	0.27	0.00	1.00
Climate-related shock	yes/no	0.37	0.48	0.00	1.00
Severe shock	yes/no	0.23	0.42	0.00	1.00
Female headed HH	yes/no	0.11	0.32	0.00	1.00
Age of HHH	Years	45.78	14.41	14.00	111.00
Education of HHH	Years	4.02	4.17	0.00	31.00
HH size	Number	6.23	3.28	1.00	46.00
HHH belongs to	yes/no	0.74	0.44	0.00	1.00

ethnic majority					
Cropland area	Hectares	2.85	5.79	0.00	300.00
Value of HH durables	USD/cap.	249.84	1436.82	0.00	79712.50
Financial assets	USD/cap.	19.04	1352.99	-80809.20	39871.63
Forest income share at village level*	USD/cap.	0.18	0.13	0.00	0.75
Informal credit facility in village	yes/no	0.48	0.50	0.00	1.00
Formal credit facility in village	yes/no	0.16	0.28	0.00	1.00
Health center in village	yes/no	0.32	0.46	0.00	1.00
Distance to district center	Minutes	110.01	147.45	0.00	1080.00
Distance to forest edge	Minutes	71.85	79.92	0.00	480.00
Region (Africa)	yes/no	0.58	0.49	0.00	1.00
Region (Asia)	yes/no	0.29	0.45	0.00	1.00
Region (LAC)	yes/no	0.13	0.34	0.00	1.00

*Excluding the observed household; HH= household, HHH= household head

On average, only 8% of households reported increased environmental extraction as their preferred shock coping strategy: other options such as reducing consumption, selling assets, or finding wage labor proved more important (see Wunder et al. 2014 for more detailed analysis). This is somewhat discouraging vis-à-vis our Hypothesis 2. However, there were also some variations in the reported coping strategies, and the regression results explaining these variations are presented in Table 9.

First, several household characteristics are affecting whether households reported to have experienced a shock (right-hand side results columns). Household size and distance to the forest edge increased the probability of shock experiences, whereas the sex of the household head (female = 1), age of household head, and the distance to the district's urban center reduced the likelihood of such reported events. Overall, African households were more likely to report such shocks than Latin American and Asian households. In other words, we should note that the sub-sample of households who reported shocks is somewhat biased (vis-à-vis average households in the sample) towards larger African households that are more distant to forest edges (and closer to cities) and headed by younger males.

With regard to the role of forests in *ex-post* coping strategies (left-hand side results columns), we find that small, well-educated, and land-endowed households are less likely to harvest additional forest resources after experiencing shocks. A high share of forest income at the village level, however, has a large and positive effect on the choice to use forests as a safety net, i.e. a pre-existing disposition to rely on forest resources may increase the probability of relying on forests also after economic shocks. Forest-based shock coping is, however, somewhat less likely at increasing distance to urban centers, suggesting that commercialization opportunities may matter in the decision process. Overall, Asian households were more likely to rely on forest-based coping than the African and Latin American households in the sample. The perceived severity of shocks, measured through a simple yes/no question, apparently did not influence the decision to turn to forest resources in response to shocks.

Table 9: Explaining the likelihood of extractive responses to self-reported shocks. Probit model

			Selection model	
Dependent variable: used forest or wild products to deal with shock			Dependent variable: self-reported climate-related shock	
	Estimate	SE	Estimate	SE
Shock severity	-0.027	(0.10)		
Female headed HH	-0.013	(0.11)	-0.093*	(0.05)
Age of HHH	0	(0.00)	-0.002**	(0.00)
Education of HHH	-0.043***	(0.01)	-0.023***	(0.01)
HH size	-0.005	(0.01)	0.013**	(0.01)
HHH belongs to ethnic majority	0.054	(0.09)	0.025	(0.06)
Cropland area	-0.079***	(0.03)	-0.004	(0.00)
Value of HH durables	0	(0.00)	0	(0.00)
Financial assets	0	(0.00)	0	(0.00)
Forest income share at village level*	2.817***	(0.53)	0.066	(0.28)
Informal credit facility in village	0.017	(0.12)	0.075	(0.08)
Formal credit facility in village	-0.299	(0.31)	-0.075	(0.13)
Health center in village	0.019	(0.13)	-0.154*	(0.09)
Distance to district center	-0.002*	(0.00)	-0.001*	(0.00)
Distance to forest edge	0	(0.00)	0.002**	(0.00)
Region (Africa)	0.284	(0.25)	0.412***	(0.09)
Region (Asia)	0.864***	(0.27)	0.147	(0.12)

Intercept	-1.699***	(0.38)	-0.552***	(0.15)
Wald chi2	90.94			
Prob > chi2	0.00			
Selectivity test	0.40			
Total N	7976			
Censored N	5004			
Uncensored N	2972			

* p<0.10, ** p<0.05, *** p<0.010; SE are clustered at village level.

In short, we find generally little support for H1: only 8% of households used environmental extraction as their preferred coping strategy in response to a shock. This does not preclude a correlation between e.g. climate-induced shortfalls in agricultural income and increased environmental extraction, but the latter is not by households ranked is the most important response to the former. However, some minority groups were significantly more likely to go first to the forest to cope with shocks: large, ill-educated, land-poor households living in market-near villages with high regular forest incomes, especially in Asia.

5.2 Observed climate shocks and income

We now turn our attention to sector income composition in response to a climate anomaly. Where in the preceding section we had looked at households' self-perceived shocks and self-stated responses, here we will turn to shifting income patterns observed in response to weather anomalies. The approach thus changes in two respects. First, the population of events is more directly weather-focused (observed climate variables) and more inclusive of subtle changes: as a direct correlation analysis reveals, many climate anomalies are not perceived as "shocks" by households, and may thus include more moderate, and possibly repetitive reallocations of production factors in response to variable weather. Second, where in the previous section we looked at what people said they did in response to the event based on their own recall, here we are modeling what they actually seem to have done – in the sense of depicting differences in income patterns in response to the observed anomaly, while trying to control for other factors of variation.[13]

In Hypothesis 3, we expected that a decline in crop income would cause an overall decline in total income, but probably cushioned by some expansion in other income components to which households would reallocate production factors because they were less severely, or not at all hit by the weather impact. We also expected that, other things being equal, extraction from bio-diverse (forest and non-forest) natural environments would be more resilient to the anomaly than agricultural activities, yet with the qualification that activities based on perennial biomass accumulation (wood extraction from forests, livestock) would also be more resistant to the changed weather than annual biomass increments (crops, food extracted from non-forest wildlands).

[13] Both approaches have their pros and cons; we would not want to rank one as universally more reliable than the other.

The most important variables used in our analysis follow in Table 10; this includes notably the variables outlined in Equation (1) on p.12. In the Appendix, we document the considerable regional variation in the sample, showing the descriptive statistics of the variables included in the analysis for each of the four World Bank regions.

Table 10: Climate, livelihoods and control variables: descriptive statistics

Variable		**Units**	**Range**
Total	Cash and subsistence annual income from all sources transformed by inverse hyperbolic sine (ihs).	ihs 2005 USD ppp	0.0-12.2
Crop	Cash and subsistence annual income from cultivating crops, transformed by inverse hyperbolic sine (ihs).	ihs 2005 USD ppp	0.0-11.6
Livestock	Cash and subsistence annual income from livestock (animal husbandry) transformed by inverse hyperbolic sine (ihs).	ihs 2005 USD ppp	0.0-11
Forest	Cash and subsistence annual income from forest extraction, including processed forest products but excluding plantation products, transformed by inverse hyperbolic sine (ihs).	ihs 2005 USD ppp	0.0-10.9
Environment	Cash and subsistence annual income from non-forest extractive sources -- grass- and bushlands, rivers, lakes, including small-scale mining, excluding aquaculture, transformed by inverse hyperbolic sine (ihs).	ihs 2005 USD ppp	0.0-12.2
Wage	Cash annual income earned from wages and salaries, transformed by inverse hyperbolic sine (ihs).	ihs 2005 USD ppp	0.0-11.6
Other	Cash and subsistence annual income from other sources such as businesses, pensions and remittances, transformed by inverse hyperbolic sine (ihs).	ihs 2005 USD ppp	0.0-11.9
temp_mean	Annual mean temperature between 1981 and 2010, linear extrapolation between grids.	°C	9.1-28.5
temp_mean.2	Annual mean temperature between 1981 and 2010 squared, linear extrapolation between grids.	$°C^2$	82.0-814.3
prec_mean	Mean annual precipitation between 1981 and 2010, linear extrapolation between grids.	m/year	0.7-3.7
prec_mean.2	Mean annual precipitation between 1981 and 2010 squared, linear extrapolation between grids.	$(m/year)^2$	0.4-13.4
temp_anomaly	Temperature deviation in the survey year from temp_mean divided by standard deviation of temp_anomaly in the period 1981 to 2010.	standard deviation	-2.5-1.4
prec_anomaly	Precipitation deviation in the survey year from prec_mean divided by standard deviation of prec_anomaly in the period 1981 to 2010.	standard deviation	-1.3-3.6
temp_interaction	temp_anomaly × temp_mean	standard deviation × °C	-57 -33
prec_interaction	prec_anomaly × prec_mean	standard deviation × m/year	-3 -6
distance_road	Distance to nearest road	Km	0-186
distance-city	Distance to nearest city	Km	1-247

Sand	Topsoil sand fraction from Harmonized World Soil Database	% wt.	0-94
Clay	Topsoil clay fraction from Harmonized World Soil Database	% wt.	0-50
Gravel	Topsoil gravel fraction from Harmonized World Soil Database	% wt.	0-32
Carbon	Topsoil Organic Carbon from Harmonized World Soil Database	% wt.	0-35
pH	Topsoil pH (H_2O) from Harmonized World Soil Database	-log(H+)	3-8
Lime	Topsoil Calcium Carbonate from Harmonized World Soil Database	% weight	0-11
Assets	The current value of all durable goods such as machinery above a value of 50 USD that a household possesses excluding buildings and land.	1000 USD ppp	1-129
AgLand	The total agricultural land that a household owns.	hectares	0-612
Education	The average years of education of all household members aged between 16 and 60 years.	Years	0-27

Table 11: The impact of weather anomalies on sector household incomes

	Without Assets							With Assets						
	Crop	Livestock	Forest	Envir-onment	Wage	Other	Total	Crop	Livestock	Forest	Envir-onment	Wage	Other	Total
Intercept	0.553	15.265***	6.459***	12.893***	-3.493	4.552*	6.675***	-0.374	12.697***	6.530***	12.915***	3.580	4.676*	6.271***
	(2.277)	(2.405)	(2.087)	(2.186)	(3.112)	(2.552)	(1.174)	(2.510)	(2.524)	(2.353)	(2.371)	(3.183)	(2.617)	(1.254)
Temp_ Anomaly	2.526***	-1.186	-1.540	3.284***	-0.721	1.665**	-0.222	2.051**	-0.891	-1.662*	3.286***	-1.477*	1.946***	-0.089
	(0.772)	(0.792)	(0.959)	(0.848)	(0.763)	(0.675)	(0.366)	(0.839)	(0.805)	(0.952)	(0.865)	(0.788)	(0.692)	(0.363)
Temp_ Interaction	-0.109***	0.065*	0.099**	-0.127***	0.054	-0.067**	0.007	-0.090**	0.054	0.104***	-0.126***	0.094***	-0.076***	0.003
	(0.034)	(0.036)	(0.040)	(0.036)	(0.033)	(0.029)	(0.017)	(0.037)	(0.036)	(0.040)	(0.037)	(0.035)	(0.029)	(0.017)
Prec_anomaly	0.875***	0.596*	-0.79***	0.605**	-0.085	0.402**	0.191*	0.930***	0.557*	-0.685**	0.692**	-0.036	0.386**	0.205**
	(0.218)	(0.314)	(0.269)	(0.265)	(0.302)	(0.180)	(0.114)	(0.226)	(0.302)	(0.277)	(0.271)	(0.298)	(0.185)	(0.103)
prec_interaction	-0.593***	-0.584***	0.350*	-0.074	0.133	-0.004	-0.049	-0.613***	-0.552***	0.311	-0.096	0.149	-0.005	-0.058
	(0.162)	(0.214)	(0.186)	(0.179)	(0.186)	(0.119)	(0.076)	(0.171)	(0.213)	(0.195)	(0.190)	(0.195)	(0.126)	(0.067)
temp_mean	0.290*	-0.972***	-0.326*	-0.832***	0.494**	0.190	-0.127	0.374**	-0.719***	-0.294*	-0.774***	-0.087	0.198	-0.082
	(0.167)	(0.201)	(0.169)	(0.171)	(0.243)	(0.203)	(0.089)	(0.184)	(0.201)	(0.175)	(0.184)	(0.247)	(0.209)	(0.087)
temp_mean.2	-0.007*	0.024***	0.007*	0.019***	-0.013**	-0.006	0.003	-0.009**	0.017***	0.006	0.017***	0.000	-0.006	0.002
	(0.004)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)	(0.002)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.002)
prec_mean	1.126	-2.621***	1.810**	0.418	3.502***	0.692	1.724***	1.228*	-2.596***	1.664**	0.408	2.374**	-0.123	1.399***
	(0.706)	(0.826)	(0.861)	(0.885)	(1.210)	(0.713)	(0.474)	(0.741)	(0.754)	(0.839)	(0.854)	(1.061)	(0.636)	(0.411)
prec_mean.2	-0.139	0.519***	-0.370*	-0.066	-0.672**	-0.221	-0.439***	-0.179	0.527***	-0.343*	-0.077	-0.371	-0.031	-0.360***
	(0.169)	(0.187)	(0.210)	(0.222)	(0.274)	(0.172)	(0.117)	(0.177)	(0.176)	(0.208)	(0.219)	(0.242)	(0.157)	(0.103)
distance_road	-0.010***	-0.007	-0.005	0.003	-0.008***	-0.001	-0.004*	-0.008***	-0.004	-0.005	0.004	-0.008***	-0.001	-0.003
	(0.003)	(0.005)	(0.005)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.006)	(0.005)	(0.004)	(0.003)	(0.002)	(0.002)
distance_city	0.003	-0.004	0.009***	-0.003	0.000	-0.003	-0.001	0.003**	-0.004	0.010***	-0.001	-0.001	-0.003	-0.001
	(0.002)	(0.003)	(0.002)	(0.004)	(0.002)	(0.002)	(0.001)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)	(0.001)
Elevation	0.100	0.555**	-0.143	-1.474***	-0.653**	-1.027***	-0.016	0.156	0.575**	-0.142	-1.517***	-0.976***	-0.972***	0.019
	(0.225)	(0.256)	(0.334)	(0.266)	(0.283)	(0.182)	(0.144)	(0.238)	(0.264)	(0.373)	(0.267)	(0.281)	(0.190)	(0.147)
Sand	-0.006	0.005	0.009*	0.005	-0.001	0.002	-0.002	-0.006	0.002	0.006	0.005	0.006	0.002	-0.003
	(0.004)	(0.007)	(0.005)	(0.007)	(0.006)	(0.004)	(0.002)	(0.004)	(0.007)	(0.005)	(0.007)	(0.005)	(0.004)	(0.002)
Clay	-0.024**	-0.003	-0.008	-0.005	0.002	-0.006	-0.012**	-0.023**	-0.003	-0.017	-0.006	0.045***	0.002	-0.007

	(0.010)	(0.013)	(0.010)	(0.011)	(0.012)	(0.006)	(0.005)	(0.011)	(0.014)	(0.013)	(0.012)	(0.014)	(0.008)	(0.006)
Gravel	-0.014	0.002	0.016	-0.023**	-0.008	0.004	0.019***	-0.012	-0.001	0.024**	-0.013	-0.001	-0.003	0.014***
	(0.011)	(0.013)	(0.011)	(0.011)	(0.014)	(0.009)	(0.005)	(0.012)	(0.012)	(0.011)	(0.011)	(0.013)	(0.009)	(0.005)
Carbon	-0.041***	-0.015	0.005	-0.026**	0.015	0.012**	0.000	-0.037***	-0.019	0.010	-0.019*	0.013	0.008	-0.005
	(0.010)	(0.015)	(0.013)	(0.011)	(0.016)	(0.006)	(0.006)	(0.010)	(0.014)	(0.013)	(0.011)	(0.015)	(0.006)	(0.005)
pH	0.274***	-0.037	-0.113	0.070	-0.146**	-0.034	0.042	0.249***	-0.033	-0.095	0.003	-0.343***	-0.057	0.035
	(0.063)	(0.080)	(0.069)	(0.084)	(0.072)	(0.049)	(0.030)	(0.072)	(0.089)	(0.075)	(0.091)	(0.079)	(0.057)	(0.033)
Lime	-0.132***	0.014	0.038	0.024	0.119*	0.075*	-0.014	-0.106**	0.023	0.066	0.089	0.061	0.049	-0.030
	(0.044)	(0.053)	(0.054)	(0.057)	(0.065)	(0.039)	(0.028)	(0.045)	(0.050)	(0.056)	(0.057)	(0.059)	(0.037)	(0.024)
East Asia	0.300	1.431***	-0.501	-1.627***	0.360	0.410	0.648***	0.355	1.301***	-0.370	-1.482***	0.243	0.432	0.647***
	(0.298)	(0.423)	(0.353)	(0.470)	(0.461)	(0.267)	(0.173)	(0.296)	(0.412)	(0.394)	(0.447)	(0.441)	(0.267)	(0.157)
Latin America	-0.217	2.231***	1.229***	0.434	1.654***	2.091***	1.576***	-0.384	1.685***	1.219***	0.426	2.276***	1.959***	1.365***
	(0.312)	(0.335)	(0.256)	(0.355)	(0.446)	(0.230)	(0.139)	(0.346)	(0.310)	(0.279)	(0.351)	(0.429)	(0.210)	(0.122)
South Asia	-0.133	0.583	0.303	-1.981***	1.331**	1.231***	0.688***	0.172	0.614	0.303	-1.829***	1.014*	1.365***	0.708***
	(0.343)	(0.543)	(0.291)	(0.566)	(0.577)	(0.246)	(0.203)	(0.359)	(0.503)	(0.336)	(0.561)	(0.541)	(0.260)	(0.194)
Household assets								-0.004	0.003	0.005	-0.006	-0.022	0.036***	0.027***
								(0.012)	(0.011)	(0.012)	(0.007)	(0.018)	(0.008)	(0.005)
Livestock								0.066*	0.405***	0.033	0.078**	-0.140***	0.018	0.118***
								(0.036)	(0.074)	(0.040)	(0.033)	(0.033)	(0.024)	(0.017)
AgLand								0.013***	0.014***	0.002	0.007***	-0.010**	0.002	0.004***
								(0.004)	(0.005)	(0.002)	(0.002)	(0.005)	(0.001)	(0.001)
Education								-0.023	0.023	-0.043***	-0.072***	0.113***	0.084***	0.049***
								(0.015)	(0.015)	(0.014)	(0.017)	(0.023)	(0.011)	(0.007)

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

For each of the sector income variables, we ran two types of regressions (Table 11): without household assets/ capital as independent variables (see the first seven result columns) and with these capital controls included (the last seven columns). This is to take into account that households *ex ante* can adapt their asset portfolios to climate changes they experienced (means).[14]

The coefficients for the response of crop income to weather anomalies and mean climate (Table 11, Column 1) are estimated with results that conform to Hypothesis H3. To depict the marginal effects of climate and weather on income, we take the derivative of equation (1) with respect to the climate or weather variable of interest.

The first derivative of equation (1) with respect to weather anomalies is

$$\frac{d\ income_{ijk}}{d\ weather_j} = \beta\ + \eta\ \ climate_j.$$

The first derivative of equation (1) with respect to climate setting weather anomalies equal to zero is

$$\frac{d\ income_{ijk}}{d\ climate_j} = \gamma\ + 2\ \delta\ climate_j.$$

To determine the sign of the weather anomaly as a function of climate means, we set the first derivative equal to zero. The temperature or precipitation level that solves the equation is the climate under which the effect of an anomaly is neutral. To find the optimal climate for a given production, we set the derivative of (1) with respect to the climate variable of interest equal to zero as well as the weather anomaly and solve for the climate variable. The result is the optimum if (1) is concave in the climate variable of interest. The marginal effects for both climate variables themselves (squared function) and for the anomalies (including interaction term) are graphically shown in Figure 1 below.

We can see in Figure 1 that the effect of unusually high temperatures (i.e. temperature anomalies) on crop income is positive in areas with mean temperatures below 23 degree Celsius and negative above. The effect of a positive precipitation anomaly increases crop income in areas with mean precipitation levels below 1500 mm and reduces crop income in areas with mean precipitation above 1500 mm. This is in accordance with the expectation that climate anomalies have a negative effect only when they cause weather to diverge further from the optimum level for crop cultivation. Crop production in our sample has its optimum at an average temperature of 21 degree Celsius. However, it is monotonously increasing in precipitation, although precision of the estimates for precipitation is low.

The coefficients of weather anomalies in the regression of livestock income are not only of numerically lower value and significance – e.g. for precipitation anomalies and temperature interaction – but also in some cases have the opposite statistically significant sign, as we had predicted in H3(iii) – such as for the squared and unsquared mean temperature estimates. This indicates an at least partially substitutive relationship between crop incomes – relying on biomass increments during the year with a weather event – and livestock – relying typically on biomass accumulated during multiple years where weather events even out. As expected in H3(i), the impact of temperature anomalies on livestock income is opposite to their impact on crop income, but the impact of precipitation anomalies is similar on both sources of income. The interpretation is that livestock is less affected by temperature anomalies than by precipitation

[14] Household assets where recorded in the first round of interviews and may therefore be regarded as exogenous to the weather shocks (as they happened thereafter) but endogenous to climate means. Note that our regressions do not include any household level controls (age, sex, size, education).

anomalies. Generally, livestock income is relatively high for both cold and hot climate extremes, as well as in very dry and very humid climates, respectively, which indicates that crop production marginally replaces livestock husbandry in areas that are climatically suitable for crop production, whereas less suited areas (further away from the for crops optimal climate conditions) are preferentially used for livestock.

For forest extractive incomes, we generally estimate coefficients with signs that are opposite those for the crop variables: five of the eight climate coefficients have opposed and significant signs, while in the remaining three cases at least one of the pairs is insignificant. Forest income thus has a similar response to temperature as livestock, and a similar response to precipitation means as crop income. Forest income increases with precipitation and reaches a maximum in regions with mean precipitation levels of about 2000 mm, but is replaced by crop production in areas with mild temperatures. This empirical pattern conforms to H3(i): not only is forest extraction less affected than crop income, but it may in some cases rise, and thus partially compensate for weather-induced crop losses.

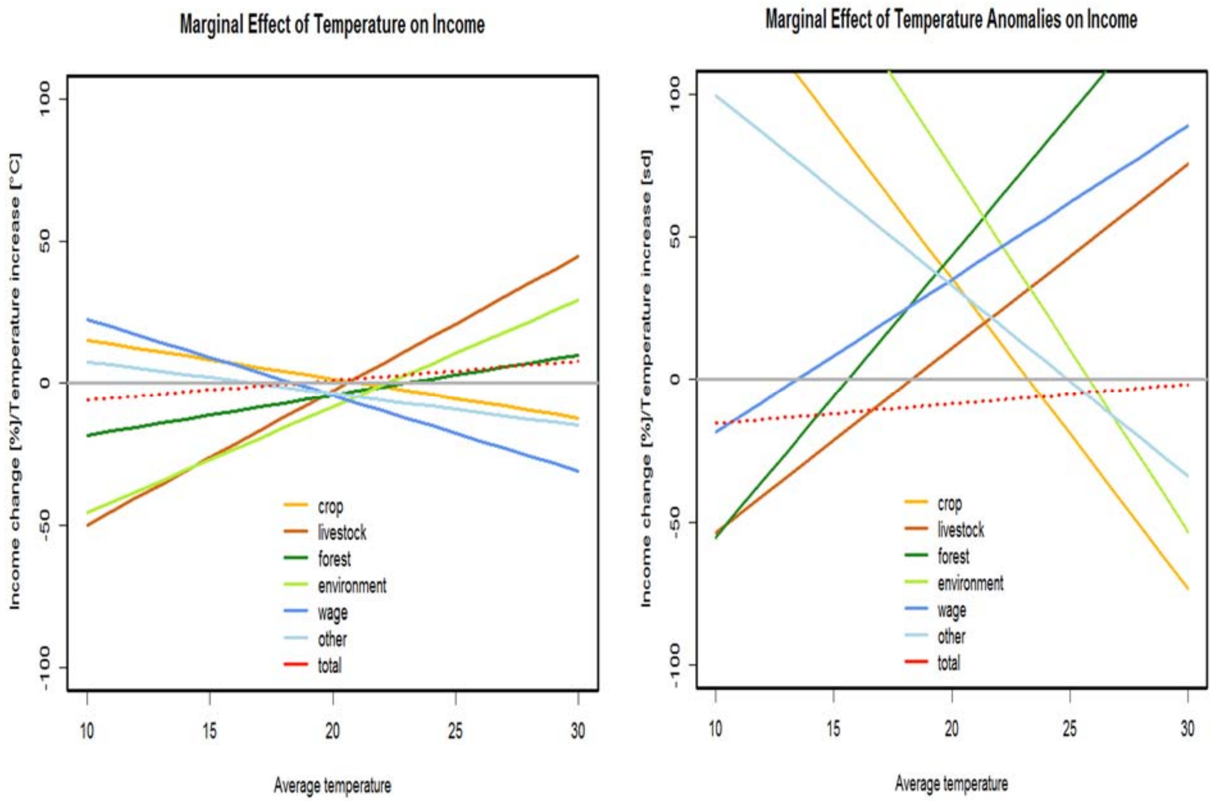
The story is quite different for non-forest environment income, which for most variables behaves much more like crop income in response to anomalies. This is what we had expected in H3(iii), due to the much greater dependence of environmental extraction outside forests on annual biomass production, especially for foodstuff. The exception is the temperature mean and squared mean variables: while for crops there is an inverted U-curve (i.e. production being largest in the middle range), for non-forest environmental extraction there is a U-curve, i.e. peaking in importance in the temperature extremes where crop cultivation may be a less relevant alternative. H3(iii) contained both ‘biodiversity’ and ‘perennial biomass’ theory elements, and in our results we can see that the perennial biomass story dominates: the estimated coefficients of forest vs. non-forest extraction and crop vs livestock tend to alternate, rather than coincide.

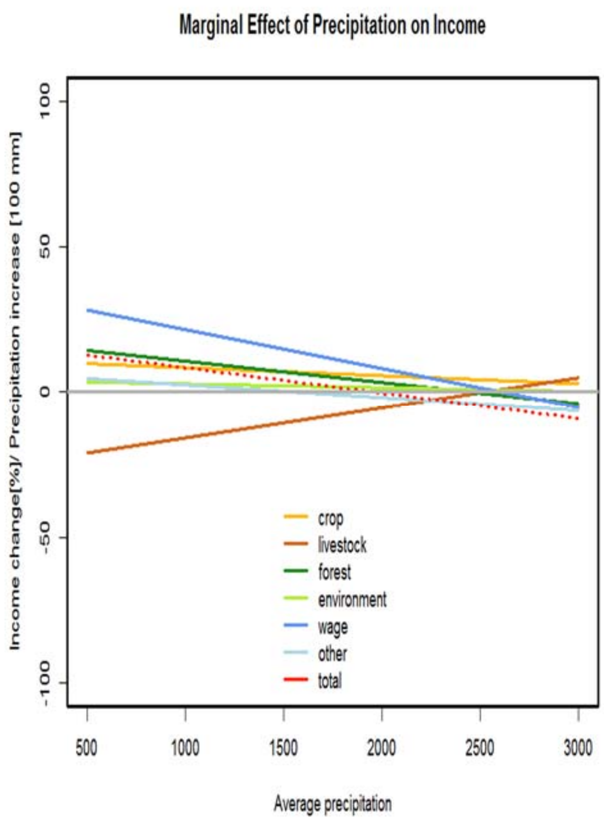
As for our two non-resource income categories, wage income and other (business, remittances, etc.) incomes are estimated with quite different signs and significance levels. While other incomes seem to behave much more in sync with the crop cycles, this does not apply to wages. An interpretation could be that the residual “other income” category picks up quite a lot of crop-dependent business activity (which will tend to suffer from an anomaly, due to its backward linkages), while wage employment seems to be sufficiently crop-independent, so as to be able to perform a partial compensation function.

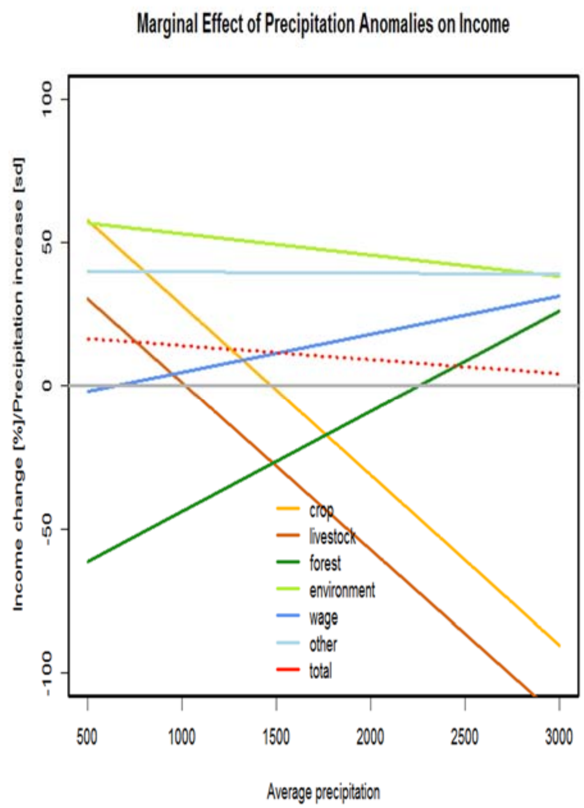
Total income peaks in climates with mean precipitation levels of just below 2000 mm, while temperature means have a limited effect. Total income is surprisingly little affected by weather anomalies: while most coefficients coincide in their sign between the crop and total income regressions, as expected in H3(ii), actually none of the anomaly coefficients is negatively significant. Only precipitation anomalies affect total income, but positively. This finding probably reflects that negative crop effects are widely being compensated across the income portfolio, which *per se* may be an encouraging observation: the rural households in our study seem to exhibit a fairly good coping capacity.

Finally, we find only a subtle difference in estimates and significance between the regression with and without household assets as control variables. However, all asset control variables are estimated with the expected and significant sign – which as such sustains our confidence in the data and model. Assets have a positively impact on total income, but variable effects on sector-wise incomes. Almost all weather and climate estimates are estimated with a slightly lower numerical value, and sometimes lower significance, when assets are included (more so for the temperature-related variables). This indicates that households over time are able to make some adjustments in asset holdings that further mitigate the already modest observed effect of climate on total income.

Figure 1: Marginal effects of climate and climate anomalies in analysis







Notes:
The marginal effect of temperature on income shows the % change in income for a 1 degree Celsius increase in long-term mean temperature (y-axis) depending on the long-term mean temperature. The marginal effect of temperature anomalies on income shows the % change in income for an increase of temperature anomaly by 1 standard deviation (y-axis) depending on the long-term mean temperature (x-axis). The methodology is analogous for the precipitation variables. Estimates are taken from the "without asset" regressions in Table 11; both significant and insignificant slope coefficients are shown.

6 Conclusions

6.1 Main findings

The purpose of this report has been to shed light on two main research questions. First, to what extent are rural households in developing countries, especially the most vulnerable, reliant on environmental extraction from natural ecosystems for their livelihoods (RQ1)? And second, what effects does climate variability have on livelihood vulnerability of the rural poor (RQ2)? In other words, RQ1 gives us a static snapshot of livelihood dependency from our large pantropical PEN sample in the years 2005-10, whereas RQ2 looks more into the dynamics between a variable climate and livelihoods.

As for RQ1, there are important arguments for taking the environment seriously as an income provider. A previous meta-study on environmental incomes (Vedeld et al. 2004) inspired our first hypothesis, namely that environmental extractive incomes would make up at least one-fifth of total household income. In fact, this extraction of wild resources (from natural forests, bushlands, fallows, etc.) provides on average as much income (27% -- of which forests 20%, non-forest 7%) as crops (26%) across our smallholder sample. While there are important site-specific differences, e.g. with respect to forest availability and resource quality, all World Bank Group (WBG) regions but South Asia exceed the 20% environmental income threshold. Among our universe of smallholders, the poorest/ most vulnerable households rely relatively more on environmental incomes, though in absolute terms they generate (and consume) less of them than the better-off households. This also has implications for our subsequent climate-related analysis (RQ2): any role played by the environmental sector carries a strong weight on household income.

If, in a bit simplified way, we were to compare the current situation to a hypothetical world without extractive incomes, then one out of seven households would be falling below the global 1.25 USD poverty line through the loss of their environmental incomes. Thanks to their fairly equal distribution, environmental incomes also contribute to improved equality in local economies. Again, if hypothetically there was no access to extractive resources, the Gini coefficient would be higher: depending on the region of analysis, between 4% and 7% of total income would have to be redistributed to restore baseline inequality levels.

As for RQ2 -- perhaps somewhat surprisingly, given the large income weight and the pattern found in numerous case studies -- environmental extraction was only for one out of 12 households (8%) the primary safety net in response to a crop, livestock, or other asset-related shock that they had stated to have been hit by over the last 12 months. Typically other responses, such as reduced consumption, running down assets, drawing on local social capital, or finding (additional) wage employment, were more important responses. Our second hypothesis of this study, regarding the alleged importance of the environment as a household safety net, did thus find little empirical support. While the contribution to current household incomes was weighty (Hypothesis 1), the importance as emergency income was less crucial (Hypothesis 2). The environmental safety-net share was higher though for households who are particularly capital-poor (cropland, education), live in Asia, and are already specialized more in forest extraction for their regular incomes.

This leads us to a more explicit scrutiny of the climate data for our sites, and their influence on household incomes (Hypothesis 3). In our analysis of climate impacts on livelihoods, we thus distinguished between long-run effects on climate means (proxying trends) and deviations in realized weather from those climate means in the particular survey year (weather anomalies). Households can *ex ante* adapt to the former, but can only cope with the latter *ex post*. Our analytical focus was on climate anomalies, analyzing how household incomes had changed in sites that had suffered a weather anomaly with likely negative impacts on crop production, controlling for other factors of variation. This analysis of anomalies could thus also become relevant to future climate change, which inter alia is predicted to cause greater climate variability and unpredictable weather patterns.

In our multiple regressions, only roughly half of the climate variables came out as significant determinants of income differences, no matter whether in the global or in regional samples, or whether we controlled for household assets (allowing for climate change adaptation) or only for other contextual variables (allowing just for coping). This is perhaps not surprising, especially given that much fewer weather stations exist in developing countries, forcing us to rely on data that is mostly based on spatial interpolations. This introduces imprecisions into the raw data underlying our analysis.

Notwithstanding these important caveats, we do find at least some plausible cross-cutting results. First, anomalies suffered during the survey year generally seem to be better predictors of income impacts than are (the so far modest) changes in climate means. However, these anomalies are causally often best combined in interaction variables with the means. For instance, a severe drought matters much more to people in a dry than in a wet area: the former will likely report it as a negative economic shock; the latter may not register any effect, or even see production gains. Climate shocks seem to matter most for people when they accentuate climatic conditions that are already fairly detached from mean temperatures and mean precipitation, respectively from the levels that are optimal for crop production.

Looking at how climate variables affected total household income and six of its sub-categories (crops, livestock, forest and non-forest extraction, wages and other incomes) gave us a more disaggregated picture. We found, as expected, that crop incomes were negatively affected by weather anomalies when the latter took temperature or precipitation further away from absolute levels that are favorable for crop production. In turn, animal husbandry seems to be more resilient to these fluctuations, being more dependent than crops upon biomass stocks that have been accumulated multi-annually. Especially rainfall anomaly effects prove to be both variable and often quite significant for sector production patterns. Although the differences between the estimations with and without household capital/ asset control variables were not large, the generally less significant results with asset controls did confirm our expectations that rural households seemingly with some success adapt their asset holdings to climate differences across our sample. Finally, we found surprisingly little significant effects from climate anomalies on total household incomes: the impacts on sector production seem to widely cancel each other out, indicating at this point fairly effective household compensatory strategies to cope with the weather anomalies.

If natural forests and other wildlands are important as income stabilizers (Hypothesis 3), why is it that only 8% of our households stated that they have used them as their primary safety net in response to economic shocks threatening their livelihoods (Hypothesis 2)? We believe that the differently perceived nature of shocks vs. weather variability may be a good potential explanation for this seeming paradox. Shocks were registered in our survey through one-year recall, and were perceived by households as discrete events with significant income shortfalls that have to be met by short-run compensatory (or other) emergency strategies: otherwise, the event would not have been flashed in the memory of the respondent. Conversely, most of the weather anomaly impacts were actually not perceived as shocks that called for emergency responses, but rather as tacit changes in production conditions that called for marginal adjustments in the household’s strategy of income generation. This interpretation is supported by the fact that different weather anomalies and the occurrence of self-perceived shocks prove to be statistically uncorrelated. In other words, to rural households coping with a shock and coping with changing weather may often be (perceived as) two different things.

6.2 Discussion and policy relevance

Perhaps the most important limitation of our results is that the study derives conclusions from cross-sectional results about the impact of variability in climate, rather than observing impacts of climate change over time in the same sites. Of course, there is always considerable interest in interpreting the former for predicting the latter. Using cross-sections for time series interpretation is common in many fields, such as the Kuznets curve for income distribution, or its environmental variant for pollution or deforestation. It is thus tempting to also use our results for a prediction of what climate change impacts would look like in the future.

Still, the interpretative transition could come to be particularly controversial here, because a lot of the damaging effects of climate change will occur through the disturbance of long-term adapted ecological systems. By "walking along a climate gradient", as we do in this report, e.g. from a temperate to a slightly hotter sub-tropical site, we are comparing two near-equilibrium long-term adapted systems with each other. This is bound to be quite different from what climate change would be like in that temperate site, because the latter will be exposed to disequilibria, rather than being able to transition smoothly to the adapted hotter site's ecological and production systems. What is more, the anthropic systems in the warmer site may also have already adapted historically in ways that make it non-comparable to the temperate site, e.g. in terms of population density being lower in the former than in the latter. If there are too many people, the extractive systems may not be able to provide a supply response in line with our cross-section predicted 'subsidy from nature' to respond to crop damages from climate change by extracting more products from natural environments. Certainly increased extraction from the environment could in some cases be a temporal pathway of adaptation to and coping with climate change, but it is not something we can prove in this study.

Nevertheless, our results could certainly be used to fine-tune the hypotheses that researchers would want a time-series study to answer in greater depth. For instance, a certain degree of substitutive relationship between agricultural and environmental incomes, and between annual biomass increment and perennial biomass production would be two such hypotheses (H3,iii) that our study points to as relevant. We did find several indications that environmental extraction from forests is a less fluctuating and more climate-resilient activity than cropping (whereas non-forest extraction of principally wild foods is almost as weather-exposed as cropping), so the former might help to stabilize livelihoods among rural smallholders when the latter becomes more fluctuating.

If this is true, a series of policies all could become potentially relevant. Conserving the integrity of these forests and wildlands will be key to sustaining an income stream that especially the poorest households rely disproportionally on. Conversely, where aggregate conservation efforts remain negligible, resource use may in many of our sites already be of degrading nature, which might well become intensified under climate change scenarios where people try to make up for crop shortfalls by increased environmental extraction (as our results seemingly suggest), while at the same time the supply of natural resources may also be negatively affected by climate effects (although likely less so than crops). Beyond of the management of the resource base, securing local people's access to extract, consume, and trade extractive resources, as well as managing the resource base themselves, will be important: too strict conservation policies could come to have a relatively drastic effect on local livelihoods, and on the ability to effectively cope with climate fluctuations. It will thus be necessary to walk a fine line of balanced conservation strategies to support local livelihoods in the best possible way.

Finally, policies that facilitate the flexible reallocation of production factors, both as an *ex ante* adaptation to long-run climatic change (barely yet observed in our sites, and thus little dealt with in this report) and as *ex post* coping with climate anomalies (analyzed more thoroughly above), may be helpful: training and education, lowering entry barriers into small businesses, provision of small-scale credits for income diversification, etc.

Education and other investments in off-farm sectors are often routinely recommended as effective adaptive and coping options for shifting labor into activities that are not climate-sensitive. While this may well be an important pathway for climate change adaptation, some of our results – e.g. the strongly significant negative effects of weather variables on “other incomes” – may also caution against any belief in quick non-farm fixes. The physical sensitivity and productive resilience to climate change is just one factor of interest here; the human preferences of settlement may be of just as high relevance: out-migration from areas with strong climatic changes will probably occur even when natural resource production is only marginally affected, although these dynamics of human settlement also lie outside of the scope of this report.

What further research needs and opportunities can we possibly point to based on this work? In addition to further time series studies, our analysis of annual weather anomalies has been one indicator in our study that does simulate an unexpected deviation from trends, which may constitute a more interesting factor of reference for climate change effects than is any so far very limited rise in mean temperatures. In prolongation of this effort, one could look further into anomalies at a finer time scale (seasons, months, in relation to dominant cropping cycles, etc.). In addition, one could also analyze which sites over time have already experienced a systematically higher incidence and/or intensity of weather anomalies, indicating another important change factor of reference.

On aggregate, our report points to an additional justification for forest conservation and sustainable use in a climate change context, going beyond the climate mitigation reasons: that the environment, and forests in particular, possibly can help rural households to better cope with climate fluctuations, at least as long as these fluctuations do not pass certain thresholds, and do not in the medium run create impacts that are too disequilibrating – which remain ‘out of sample’ data points in our study that we can hardly extrapolate. Eventually time-series studies will be needed to consolidate this hypothesis and to quantify the likely thresholds and disequilibrating effects for different climate zones of the developing world. Meanwhile, given the caveats mentioned, our study provides an overall cautiously optimistic picture regarding the flexibility of rural livelihoods to cope with and respond to the *de facto* climate variability that we have seen over the last three decades, with forests and the environment playing an essential part of the story.

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Appendix: Descriptive Statistics

Table A1a: Summary statistics regression variables, Latin America sample (N=848)

	Mean	Std.dev	Min	Max
Total income (USD per aeu, PPP)	4 850	6 491	225	76 535
Hh size (PEN aeu)	3.75	1.77	1.00	11.30
Age of hh head (years)	44.56	14.28	18	92
Share female hh	0.07	0.26	0	1
Education hh head (years)	5.57	3.92	0	18
Share of hh heads born in village	0.33	0.47	0	1
Share of hh heads belonging to largest ethnic group	0.83	0.37	0	1
Agricultural land owned, in ha	3.38	6.40	0	81.35
Livestock owned, in TLU	3.10	12.43	0	254
Other assets owned, (USD per aeu, PPP)	1 462	4 741	0	79 713
Share of hh with wage income	0.78	0.41	0	1
Share of hh with with household business	0.23	0.42	0	1
Distance forest (minutes walking from hh)	0.65	0.96	0	5.00
Distance village center (minutes walking from hh)	0.49	0.69	0	5.00
Village market integration (mean cash/total income)	0.74	0.11	0	0.96
Electrification. Share of hh in the village with electricity	0.47	0.44	0	1
Precipitation (village mean 1981-2010)	2 272	537	1 729	3 667
Temperature (village mean 1981-2010)	23.41	3.15	15.46	26.51

Table A1b: Summary statistics regression variables, South Asia sample (N=1094)

	Mean	Std.dev	Min	Max
Total income (USD per aeu, PPP)	1 459	1 370	129	26 156
Hh size (PEN aeu)	3.74	1.45	1.00	11.90
Age of hh head (years)	49.38	14.81	14	97
Share female hh	0.11	0.32	0	1
Education hh head (years)	2.49	3.69	0	15

Share of hh heads born in village	0.78	0.42	0	1
Share of hh heads belonging to largest ethnic group	0.82	0.38	0	1
Agricultural land owned, in ha	0.93	1.72	0	15.53
Livestock owned, in TLU	1.10	2.16	0	42.22
Other assets owned, (USD per aeu, PPP)	926	2 998	0	49 580
Share of hh with wage income	0.78	0.41	0	1
Share of hh with with household business	0.24	0.42	0	1
Distance forest (minutes walking from hh)	0.58	0.42	0	3.00
Distance village center (minutes walking from hh)	0.40	0.54	0	4.00
Village market integration (mean cash/total income)	0.60	0.13	0	0.86
Electrification. Share of hh in the village with electricity	0.42	0.41	0	1
Precipitation (village mean 1981-2010)	1 882	673	1 177	3 197
Temperature (village mean 1981-2010)	21.63	6.83	9.05	27.55

Table A1c: Summary statistics regression variables, East Asia & Pacific sample (N=1297)

	Mean	Std.dev	Min	Max
Total income (USD per aeu, PPP)	1 675	1 922	0	39 619
Hh size (PEN aeu)	3.41	1.16	1.00	9.50
Age of hh head (years)	43.88	12.93	18	90
Share female hh	0.10	0.30	0	1
Education hh head (years)	4.96	3.51	0	17
Share of hh heads born in village	0.51	0.50	0	1
Share of hh heads belonging to largest ethnic group	0.89	0.32	0	1
Agricultural land owned, in ha	0.65	1.10	0	12.35
Livestock owned, in TLU	0.67	0.81	0	10.57
Other assets owned, (USD per aeu, PPP)	569	1 237	0	20 530
Share of hh with wage income	0.61	0.49	0	1
Share of hh with with household business	0.26	0.44	0	1
Distance forest (minutes walking from hh)	0.43	0.39	0	3.50
Distance village center (minutes walking from hh)	0.25	0.32	0	2.00
Village market integration (mean cash/total income)	0.67	0.18	0	0.98
Electrification. Share of hh in the village with electricity	0.47	0.42	0	1
Precipitation (village mean 1981-2010)	1 981	607	1 144	3 238
Temperature (village mean 1981-2010)	25.29	2.93	18.89	27.68

Table A1d: Summary statistics regression variables, Africa sample (N=4090)

	Mean	Std.dev	Min	Max
Total income (USD per aeu, PPP)	1 015	2 585	13	100 351
Hh size (PEN aeu)	4.41	2.17	1.00	20.00
Age of hh head (years)	45.48	14.67	14	111
Share female hh	0.13	0.34	0	1
Education hh head (years)	3.96	4.13	0	18
Share of hh heads born in village	0.55	0.50	0	1

Share of hh heads belonging to largest ethnic group	0.66	0.48	0	1
Agricultural land owned, in ha	1.20	2.93	0	106
Livestock owned, in TLU	0.84	1.60	0	26.05
Other assets owned, (USD per aeu, PPP)	165	789	0	37 879
Share of hh with wage income	0.53	0.50	0	1
Share of hh with with household business	0.46	0.50	0	1
Distance forest (minutes walking from hh)	0.59	0.79	0	5.00
Distance village center (minutes walking from hh)	0.41	0.57	0	4.00
Village market integration (mean cash/total income)	0.52	0.14	0	0.90
Electrification. Share of hoh in the village with electricity	0.05	0.17	0	1
Precipitation (village mean 1981-2010)	1 170	260	658	2 140
Temperature (village mean 1981-2010)	23.39	4.13	13	29

Table A1e: Summary statistics regression variables, global sample (N=7392)

	Mean	Std.dev	Min	Max
Total income (USD per aeu, PPP)	1 642	3 309	0	100 351
Hh size (PEN aeu)	4.06	1.93	1.00	20.00
Age of hh head (years)	45.67	14.45	14	111
Share female hh	0.12	0.32	0	1
Education hh head (years)	4.10	4.03	0	18
Share of hh heads born in village	0.55	0.50	0	1
Share of hh heads belonging to largest ethnic group	0.74	0.44	0	1
Agricultural land owned, in ha	1.31	3.28	0	106
Livestock owned, in TLU	1.11	4.54	0	254
Other assets owned, (USD per aeu, PPP)	500	2 180	0	79 713
Share of hh with wage income	0.61	0.49	0	1
Share of hh with with household business	0.36	0.48	0	1
Distance forest (minutes walking from hh)	0.57	0.72	0	5.00
Distance village center (minutes walking from hh)	0.39	0.55	0	5.00
Village market integration (mean cash/total income)	0.58	0.17	0	0.98
Electrification. Share of hh in the village with electricity	0.23	0.37	0	1
Precipitation (village mean 1981-2010)	1547	628	658	3667
Temperature (village mean 1981-2010)	23.47	4.50	9.05	28.54