How do rural households respond to economic shocks? Insights from hierarchical analysis using global data

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Abstract

Unanticipated events can cause considerable economic hardship for poor rural households. Some types of negative shocks, for example weather-related agricultural losses and vector-borne diseases, are expected to occur more frequently as a result of climate change. This paper measures the role of household- and location-specific characteristics in conditioning behavioral responses to idiosyncratic and covariate shocks. We use data from more than 8000 households in 25 developing countries, compiled in the global database of the Poverty Environment Network (PEN). We employ a hierarchical multinomial logit model to identify the importance of characteristics observed at different levels of aggregation on a set of responses to economic shocks. Results indicate that in response to idiosyncratic shocks, households tend to deplete financial and durable assets, whereas covariate shocks predominantly result in reduced consumption. Households in sites characterized by high asset wealth tend to respond to shocks more proactively than in sites with average or below average asset wealth; savings emerge as an important determinant of shock response behavior at the household level. We also find that a higher concentration of land ownership at the village level reduces the prevalence of natural resource-based coping strategies. Overall, rural households are less reliant on natural resource extraction for coping than expected from the case-study literature. Our findings have implications for rural development and climate change adaptation strategies.

JEL codes: I3, O1, Q2

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1. Introduction

Over 70% of the share of the global population earning less than US$ 1.08 a day lives in rural areas (Ravallion et al., 2007). These poor rural households are thought to be particularly vulnerable to economic shocks. This is not only because they tend to have fewer means to cope with economic hardship than the non-poor, but also because they rely on economic activities, such as agriculture and forestry, for which returns are highly variable. Moreover, because climate change is expected to increase the frequency of extreme weather events, especially in the rural tropics, the vulnerability of resource-dependent people is likely to increase (Stern, 2007). Apart from the broad measures necessary to alleviate rural poverty, therefore, climate change calls for specific actions to reduce the vulnerability of poor rural households to economic shocks.

Vulnerability is commonly understood as a function of exposure, sensitivity, and adaptive capacity. Biophysical climate change research has produced much evidence with respect to exposure and sensitivity of rural households to extreme weather events and their potential economic consequences at regional and global scales (Parry et al., 2007). According to the IPCC's fourth assessment report, Africa is considered the most vulnerable continent to climate change. Temperature and water stresses, which are common in arid and semiarid Africa, are expected to worsen under climate change, thereby generating more frequent covariate shocks, such as crop failure. Due to widespread poverty and natural resource degradation, poor infrastructure, and deficient governance and institutions, little scope exists for the development of adaptive strategies at the local level. For example, recent evidence suggests that widespread irrigation development in sub-Saharan Africa would only partially offset climate-related losses (Ward et al., 2011). Scenarios for Asia and South America are somewhat less pessimistic, in part because most observers assume greater adaptive capacity due to higher average levels of development, diversification, and more abundant natural resources per capita, especially in Latin America.

Adaptive capacity is related to multiple concepts including coping ability, management capacity, stability and robustness, as well as broader socio-economic and institutional features of the landscape (Smit and Pilifosova 2003). Direct emprirical measures of adaptive capacity are thus difficult to obtain and most evidence regarding its determinants are based on individual case studies (Smit and Wandel, 2006). However, adaptive capacity also tends to be reflected in the choices that people make when they respond to shocks. Household coping strategies may depend on multiple factors, including the type and size of shock, individual household characteristics, and context factors, such as access to natural resources, markets, and public services. Dercon (2000) identifies several broad categories of risk coping strategies. Ex post responses often involve the liquidation of assets, the accumulation of which may have been part of a more complex ex ante strategy to generate self-insurance. Likewise, income smoothing as a risk-coping strategy may manifest itself in terms of permanent income portfolio adjustments, e.g. diversification and choice of low-risk agricultural activities, or as a direct response to a shock, e.g. off-farm work after crop failure. Finally, many rural households depend on informal risk sharing mechanisms and safety nets, e.g. seeking external help from friends and families, to buffer shocks. Safety net functions have also been attributed to natural resources, including forests, which in various case studies have been shown to provide additional income after negative shocks (Pattanayak and Sills, 2001; Takasaki et al., 2004; Debela et al. 2012), or to be used less in the wake of positive income shocks (Fisher and Shively, 2005). Failure to respond actively to a shock, or to reduce consumption in response to an income shortfall, has been associated with negative effects on nutrition and health (Rose, 1999). In a study from Tanzania, Beegle, Dehejia, and Gatti (2006) demonstrate how agricultural shocks can precipitate greater use of child labor, thereby disrupting schooling and undermining long-term investments in human capital.

Several case studies have looked at the direct shock responses of rural households as a means to understand underlying coping strategies (McSweeney, 2004; Paumgarten, 2005; Rose, 2001; Völker and Waibel, 2010). Not surprisingly, conclusions regarding the relative importance of specific shock responses differ widely. The emerging “safety net” literature generally confirms the importance of forests in helping rural households to cope with shocks, but few studies compare different sites to measure the role of contextual factors in affecting response behavior (Sunderlin et al., 2005). The forest safety net function is also seldom evaluated against other potentially available response options to assess the relative importance of forests.

This paper contributes to the general literature on household response to shock as well as the specific literature on forest use in marginal environments. We use a new global data set compiled by the Poverty and Environment Network (PEN) of the Center for International Forestry Research (CIFOR).[1] This global PEN dataset contains detailed data on income sources and household characteristics, collected quarterly from more than 8000 households in 24 countries. Data include self-reported responses to a large variety of covariate and idiosyncratic shocks. We use these data to estimate a series of multilevel regression models. Our findings underscore the importance of assets as a safety net, but also suggest that low-income households in rural areas are still widely forced to reduce consumptions after shocks. Natural resources represent a less important than expected safety net from a global perspective, but can still be important for coping in specific circumstances. Village-level factors such as informal credit institutions and land property rights regimes emerge as potentially important entry points for policy action in the face of climate change.

2. Empirical strategy

The global PEN data base is a collection of independently conducted field studies derived from a common questionnaire and a set of centrally-determined sampling criteria. PEN sites cover the major sub-continental areas in Africa, Asia and Latin America (Figure 1; one dot may represent more than one site). The PEN database contains survey data on 8000+ households in 58 study sites in 25 developing countries. In general, study localities were chosen so as to: (i) display at least a minimum level of forest dependence; (ii) meet specific criteria relevant to the topics of each individual study; and (iii) meet PEN's site sampling criteria of representation and variation. Regarding representation, the aim was to avoid special cases, e.g. areas with unusually valuable

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forest products, unusually favorable or unfavorable conditions for income generation, or a history of large-scale donor intervention or activity. The non-random nature of study site selection and limited number of sites per country imply that one cannot extrapolate conclusions study sites to entire countries. Furthermore, the sampling approach created a bias toward forest-based coping in the sample. The sites are also generally dominated by smallholders; sites dominated by large-scale agribusiness farming were not included.

Regarding variation, site selection occurred along key gradients, such as market distance, vegetation types, land tenure and institutions, population density and growth, predominance of ethnic groups and commercial stakeholders, sources of risk, and levels of poverty. The goal was to choose sites that would be broadly representative of a larger underlying population – e.g. a district or province within the country being studied. Not all gradient variations are found within any single study area, and often gradients correlate. For example, areas remote from markets tend to be poorer in income but richer in natural vegetation, less densely populated, but with larger shares of indigenous people. While PEN sites and villages were thus selected according to explicit stratification criteria, the within-village selection of households followed random sampling, using household lists and pre-existing censuses as sample frame. To be included in the global PEN data set, a minimum sample of 100 households was required. Most contributing studies had larger samples, with an average of roughly 250 households per site. Participating households were randomly selected from pre-existing village household lists or from new village censuses.

Table 1 presents evidence from the pooled PEN sample regarding the proportions of households that reported shocks and specific shock-mitigating activities. Households were asked at the end of a 12 month period with quarterly income surveys if they had suffered any significant income shocks -- and if yes, what type of shock, what degree (intermediate vs. severe), and how they had responded to it. We follow the conventional terminology that distinguishes between covariate and idiosyncratic shocks. Covariate shocks (e.g., weather or price effects) have the potential to affect an entire community, whereas idiosyncratic shocks (e.g., death or illness) are more likely to affect individual households. In the global PEN data base, covariate shocks include crop failure as well as major livestock or durable asset loss. Idiosyncratic shocks that affect the family labor force include death and illness. Asset-related idiosyncratic shocks include the loss of employment, expropriation of land, fines, and default of debtors. During the survey, households were asked to self-report their responses to these shocks. Responses were categorized as follows. *Asset Depletion* includes reports of spending savings or selling or renting out land or other assets. *Reallocated Labor* represents the initiation of new on-farm or off-farm activities, or changes in activities. *Sought Outside Help* includes reports of seeking assistance from friends, family members, or organizations, as well as borrowing. *Used Wild Products* incorporates harvesting wild products from forests and/or non-forest environments. And *Reduced Consumption* represents household reports of reductions in spending or the number of meals prepared and consumed; it also includes cases where no other specific response was recorded. Our empirical goal is to understand systematic patterns of these responses in the dataset.

Several features of the data in Table 1 are noteworthy. First, covariate shocks (mainly crop failure) are the most widely reported shocks; they constitute 50% of reported shocks in the sample (1910 out of 3847, including multiple shocks per household). Idiosyncratic shocks affecting household labor are the second most widely reported category. Second, *Asset Depletion* stands out as the most frequently reported response to idiosyncratic shocks, and *Reduced Consumption* is the most frequent response to covariate shocks. Only a small share of shocks induced *Used Wild Products*, which is somewhat surprising given the number of studies that emphasize this particular option for rural households. Wild product use seems to be most important as a response to covariate shocks, whereas few households *Sought Outside Help* in response to this type of shock. This makes sense intuitively, because extraction of wild products can be a time-intensive activity, which may seldom be an option if shocks affect a family's labor availability.

Building on these stylized features of the sample, our goals are first to explain these shock response patterns, and second to examine whether variables broadly construed to lie within the domain of policy makers might influence responses and – by extension – household welfare. We test several hypotheses from the literature on risk coping strategies in general, and studies on the safety net function of forests in particular. First we investigate whether poorer, younger, and less educated households tend to rely more on natural resources than longer-established and better-off households. While this notion has been confirmed in several studies (Debela et al., 2012; McSweeney, 2004; Takasaki et al., 2004), others (e.g. Pattanayak and Sills, 2001) have reported that older and better-off households may use forests at higher rates, presumably because longer residencies confer greater benefits from extractive activities that require local knowledge or customary access rights. But, forest reliance may also be the result of specialization in one or more particularly valuable forest product. This leads us to establish a second more general hypothesis, namely that shock responses are correlated with pre-existing livelihood strategies. In other words, we test whether households that are well-endowed with assets (or already derive high incomes from natural resource extraction) tend to respond to shocks through more asset liquidation (or greater use of natural resources) than asset-poor households. A third hypothesis is that village level factors such as public services, infrastructure, and distance to markets affect responses to a greater extent than household level characteristics. While such a pattern may not hold generally, we expect village- or site-specific factors to sometimes dominate household-level determinants of shock responses, especially where institutions such as formal credit facilities represent reliable means to smooth consumption following shocks.

3. Data and Methods

Table 2 reports descriptive statistics for all explanatory variables used in the subsequent analysis. Apart from directly observed farm-household characteristics we include an asset index, which we constructed from household durable and livestock asset counts using principal component analysis. Village-level variables include the gini coefficient of land ownership and indicators likely to influence household vulnerability, such as the existence of a health center, credit facilities, and distances to major product markets.

The stated shock response data summarized in Table 1 can be characterized as unordered or multinomial choice data. A typical approach to modeling unordered choices is the multinomial logit model (MNL). Hedeker (2003) proposed a mixed-effects MNL model that extends the standard model to allow for varying slope and intercepts at different levels of aggregation, e.g. households clustered in villages and villages clustered in sites. The model is:

$$\Pr\left(y_{ij} = c \mid \beta\right) = \frac{\exp(z_{ijc})}{1 + \sum_{h=1}^{C} \exp(z_{ijh})} \qquad \text{for } c = 2, 3, \ldots, C \tag{1}$$

where y_{ij} are nominal response values for household j in village i, and c designates response categories. The model is made hierarchical by specifying each z element as its own function:

$$z_{ijc} = w'_{ij}\,\alpha_c + x'_{ij}\,\beta_{ic} \tag{2}$$

where w and α are vectors of predictors and unknown fixed regression coefficients, respectively. Using this set-up, x is a design vector that links households to villages and β is a vector of unknown random coefficients to be identified.

The properties of (1) imply that the odds of observing any two choices are given by a ratio:

$$\frac{\Pr\left(y_{ij} = 1 \mid \beta\right)}{\Pr\left(y_{ij} = 2 \mid \beta\right)} = \exp(z_{ij1} - z_{ij2})\,. \tag{3}$$

The odds ratio of two choices does not depend on other available choices. This property of the MNL is referred to as Independence of Irrelevant Alternatives (IIA). Grilli and Rampichini (2007) argue that the introduction of random terms in the linear predictors allows one to at least partially relax the IIA assumption in the multilevel formulation of the MNL. Nevertheless, one must be concerned about violating IIA if there is reason to expect that the choice between two options in the choice set is influenced by a third option. The choices should therefore be distinct enough to not represent perfect substitutes (McFadden, 1973).

While none of the options in our choice set would qualify as clear substitutes, IIA could potentially be violated, for example, if the choice between two categories was affected by, say, the ability to reallocate labor. Whether or not IIA is violated in a specific circumstance ultimately depends on empirical matters and the structure of the data. This has led to the development of statistical tests, such as the Hausman-McFadden test which examines changes in estimated parameters as a result of changes in the choice set (Hausman and McFadden, 1984). The reliability of the Hausman-McFadden test has, however, been questioned on the basis of Monte Carlo simulations (Vijverberg, 2011). An alternative to the MNL that relaxes the IIA assumption is the computationally more complex multinomial probit model (MNP). In a comparative analysis, Dow and Endersby (2004) conclude that IIA is not particularly restrictive in most applications.

4. Results

Implications of assuming IIA

We first estimated a standard MNL model excluding village level predictors and tested for IIA using the Hausman-McFadden test.[2] Test statistics varied widely depending on the base category used in the MNL estimation and suggest evidence both for and against IIA. To assess the implications of erroneously assuming IIA, we estimated an identical MNP model to compare results. These comparisons, in terms of differences in coefficient values (α), statistical significance (σ), and signs (+/-), are reported in Table 3. All significant coefficients in the MNL model are also significant in the MNP specification, and only one coefficient in the first response category (*Used Wild Products*) is significant only in the MNP specification. With only one exception, coefficients have the same signs in both models. Differences in significant coefficients range from 1 to 21%

[2] Results in this paper include standard MNL and MNP as well as multilevel MNL specifications generated using Stata (StataCorp, 2007; Rabe-Hesketh, 2001), MIXNO (Hedeker, 1999), and R (R Development Core Team, 2006).

with MNL coefficients being almost uniformly smaller than MNP coefficients. Hence, if the MNL specification violates IIA, implications arise primarily for prediction purposes. The two models, by and large, suggest identical patterns of behavioral response to the analyzed shocks. Since no available algorithm consistently converged on a fully-specified multilevel version of the MNP model, we use the MNL specification in our subsequent discussion of results.

Multilevel determinants of shock response in a random-intercept model

Table 4 presents results of a three-level random-intercept MNL specification using the full set of variables reported in Table 2. Multiple weighted household level shock responses (n=2029) represent the first level, and villages (n=230) and sites[3] (n=27) represent the second and third levels respectively. The response option *Reduced Consumption* was chosen as a base category, i.e. the coefficients for each response category need to be interpreted vis-à-vis the option of non-action. Negative coefficients in Table 4 suggest lower probabilities relative to non-action and positive coefficients suggest higher probabilities. Among the household-level variables we find shock type and severity to play important roles in conditioning response. In particular, households tend to reallocate labor and seek external help in response to severe shocks that cannot be addressed by using natural resources or selling assets. Covariate shocks, the most frequently reported type, , seem to almost generally induce non-action rather than any of the active response options. We expected negative signs for covariate shocks under the *Asset Depletion* and *Sought Outside Help* categories, because these responses may be of less use when a whole village or region is affected, which is typically the case for this shock type.[4] Idiosyncratic shocks affecting the household labor force have strong positive association with asset depletion, labor reallocation and pursuit of outside help. This finding appears intuitively meaningful, and suggests that households can buffer against

[3] Some sites consist of several heterogeneous sub-sites, which eventually justifies treating them as independent sites, which was not done in this analysis.

[4] Natural resource extraction and labor reallocation would appear nonetheless still as intuitively attractive options in some settings, but depending on the actual shock, specific site level-patters may not have been captured in the random intercept specification.

idiosyncratic losses by engaging in the local labor market, selling livestock to other village members, or even asking neighbors for help.

Overall, few of the household characteristics included in the model seem to provide statistically meaningful importance for shock responses, although older household heads are less likely to reallocate labor in response to shocks. However, it is possible that household characteristics condition responses, but that these patterns are not revealed in this model. The last set of farm-household related variables exhibit interesting patterns. It appears that households with small agricultural plots tend to rely more on natural resource extraction than households that specialize in agriculture. Households that engage less in agriculture or lack access to more land resources also tend to more heavily rely upon outside help following shocks.

The average share of environmental income strongly predicts wild product use in response to shocks. We suspected an inverse causal relationship for this variable and tested whether households that received shocks differ in average environmental income from households that did not experience shocks. However, the pattern is not confirmed in the data. Hence, it appears that specialization in natural resource extraction, whether part of a long-term adaptation strategy or not, plays an important role in determining the safety-net functions of forests and other natural resources. Interestingly, a low forest income share reduces the probability that a household will deplete assets, whereas the share has a positive correlation with savings. Households that accumulate monetary assets to spend in time of shocks thus seem to be less specialized in natural resources (mainly forest) use. High savings also reduce the probability that a household engages in labor reallocation.

Our asset index reflects durable asset wealth, rather than monetary or productive assets. The index does not reliably predict choices among responses. This is somewhat surprising, mainly because the index has positive correlations with all shock responses in non-hierarchical models. A natural conclusion from this pattern would be that poorer households (in terms of asset wealth) are more likely to weather shocks by reducing consumption rather than adopting some sort of active response either due to a lack of options or because of limited capacity. Why this relationship vanishes when we shift to a hierarchical model with random intercepts, especially when the model provides greater explanatory power, may reflect the fact that intra-site variability of asset wealth is low or similar across many sites, whereas high variability exists between some sites in our global sample. Site level random intercepts may then work against a relationship that only exists across sites.[5]

Among the village level variables included to predict village level intercepts, we find the availability of informal credit infrastructure to induce households to seek outside help as well as deplete assets in times of economic hard ship. This makes sense in particular, because the option of taking a credit was included in the *Sought Outside Help* response category, but it is still interesting to note that informal credit institutions appear to be better safety net providers than formal alternatives. Whether the presence of informal credit does actually favor *Asset Depletion* in response to shocks, or whether assets need to be depleted to pay high interests on informal credits, cannot be answered by our model.

The reallocated labor response category includes the options *Started New Business* and *Did Extra Casual Labor Work*. Distance to commercial centers may increase the probability of households to reallocate labor, which perhaps explains the positive significant relationship between distance to markets for extractive products and this response category.

High concentration of land ownership at the village level reduces the probability of natural resource extraction relative to non-action. This new piece in the puzzle of shock response seems to suggest that the safety net function of natural resources (especially forests) may be limited by local tenure and land access conditions. This may be relevant particularly for poor households, although

[5] A regression with random coefficients produces results that are nearly identical in sign, magnitude and significance to the model with random intercepts. This probably reflects the fact that most of the observed (and explained) variance occurs at higher levels of nesting. A non-hierarchical MNL incorporating site-specific shifters generates results that are more pronounced in terms of the influence of household-specific factors, which likely reflects the fact that the regression incorporating site-specific binary indicators attaches the same weight to relationships independent of the number of observations, while the hierarchical regression implicitly weights the relationships by the number of observations at each level.

the asset wealth index included in this model specification does not suggest clear patterns with respect to shock response.

How well does this model predict actual shock responses? Figure 2 depicts predicted (posterior) probabilities for each response option, reported by site. Sites are ordered according to continents from left to right: Latin America, Asia to Africa. The predicted probabilities for most of the shock response categories are rather low, which reflects the fact that the second most common response *Reduced Consumption* is the counterfactual used in the analysis. *Wild Product Use*, *Asset Depletion*, and *Reallocated Labor* are all eventually predicted with probabilities greater than 0.5, but by far the majority of predicted values lies below the 0.5 probability limit. The highest predicted probabilities occurred in Asian and African countries (particularly in Nepal, Ghana, and Burkina Faso) especially in the asset depletion category. As can be inferred from this figure, households in Asian and African countries (left in Figure 2) also reported considerably more shocks than in Latin American countries (right in Figure 2), both in relative and absolute terms. We conclude that the model is helpful in teasing out which of the observed variables increases the probability of a particular response vis-à-vis other possibilities, but it performs rather poorly as a predictive tool.

Finally, we take a look at the site-level random effects. Figure 3 shows the 27 site-level random effects by country, ordered by the size of the effect. The random effects vary between -1 and 2, with a substantial proportion of random effects being larger than covariate coefficients or category specific intercepts (see Table 4). This suggests important unobserved site-level effects in some of the study sites. Unfortunately, no set of site-specific variables (e.g., average rain fall, see Figure 3) that might be employed to help explain these patterns was available at the time of this analysis. The random effects also do not suggest any particular pattern with regard to countries. Latin American, Asian, and African countries appear among negative, near zero, and positive random effects, which reconfirms the notion offered above that sites are not representative of countries in terms of shocks and responses to them. In fact, differences between sites seem to be greater than differences between countries or even continents, at least with respect to shock response behavior.

5. Discussion and conclusion

This paper presents an analysis of stated shock response behavior recorded in the global Poverty Environment Network (PEN) data base. The data covers a large variety of shocks and response options, which broadly confirm theoretical expectations regarding shock response behavior. For the purpose of analyzing the determinants of this behavior, we used a multilevel multinomial logit (MNL) model incorporating household- and village-level covariates. We quantitatively assessed and discussed the implications of assuming Independence of Irrelevant Alternatives (IIA) in the MNL model and concluded that, in the current case, any potential violation of this assumption is unlikely to undermine conclusions based on this analysis.

Based on our global sample we find some, but not all notions from case-study based assessments confirmed. For example, households headed by older individuals are generally less likely to engage in natural resource-based shock-coping strategies than younger households (McSweeney, 2004; Fisher and Shively, 2005). Among others, this attribute (younger household head) is typical of households in the early stages of the agricultural household life cycle, characterized by young families that have not yet had the time or access to sufficient labor or land / capital accumulation (Perz, 2001, McSweeny, 2004). Because this leaves fewer resources to endure shock, households often turn to off-farm sources (Ellis, 1998). Household head's education, however, is not significantly related to any specific shock response behavior, contrary to the findings of Völker and Waibel (2010) in the uplands of Vietnam and Fisher et al. (2010) who found education to be inversely related to forest extraction activities. In these studies education could be linked with intelligent farm management that provides more educated household heads with other coping strategy options than forest extraction (Volker and Weibel, 2010). The first of three hypotheses set out in this paper can thus only partially be confirmed.

In general, shock types and severity turn out to be among the most powerful predictors of shock responses. Responses to idiosyncratic shocks seem to be more diverse than those to covariate shocks, simply because many pro-active response options, such as getting help from neighbors, reallocating labor and liquidating assets locally are of less use when a whole village or large parts of it are affected. This is potentially bad news in the context of climate change, which is expected to increase the incidence of covariate shocks in all three continents under study, and in Africa in particular. Severe shocks induce primarily two types of responses, namely labor reallocation and seeking outside help, which both tend to be preferred among households in this global sample as a response to idiosyncratic shocks. Hence, wherever climate change scenarios predict more frequent *and* more severe covariate shocks, local adaptive capacity, i.e. the size of the set of available response options, is likely to be very limited. In line with the conventional wisdom, this would appear particularly true for poor households in areas with low natural resources quality, which may often find themselves short of alternatives to reducing consumption after shocks. Related to this, based on simulation modeling, Zimmerman and Carter (2003) report the somewhat counterintuitive finding that poor households tend to smooth assets rather than consumption, especially as compared with wealthier households. The high relative importance of reducing consumption in combination with the role of savings in inducing asset depletion in our global sample of predominantly low-income households seems to offer supporting empirical evidence for Zimmerman and Carter’s finding. Our model, moreover, confirms our second hypothesis, by suggesting that the presence of savings induces asset depletion, and environmental income reliance favors wild product use in times shock. Both these response categories thus seem to be related to ex ante coping or preexisting livelihood strategies.

The low occurrence of natural resource based shock responses in this global sample is nonetheless surprising, given that site selection is biased towards landscapes rich in forest resources. Forest abundance may indeed be merely a favorable, but not a sufficient condition for the resilience of adjacent communities. For these communities to utilize forests as safety nets, various other conditions must be met, including high forest quality with valuable species (e.g., medicines, seeds, fruits, game, construction material that can be immediately harvested when needed) occurring in sufficient densities, local extractive knowledge, and solid demand for forest products on local markets. Non timber forest products (NTFPs) in particular have been shown to be important safety nets in this capacity (e.g., Falconer, 1992; Almeida, 1996; Ogle, 1996; Godoy et al., 2000).

Turning to our third hypothesis on the role of village and site-level factors, we find two of the village-level predictors in our hierarchical MNL model to be significant and positively related to active shock responses. Both would appear important entry points for climate change adaptation strategies. First, as opposed to formal credit, the existence of informal credit institutions clearly favors response options that involve external support to shock coping. Such institutions may be the result of high social capital in some villages, but also tend to depend on a favorable climate for financial exchanges in the wider economy (Pender, 1996). Informal credit, however, also tends to be more expensive (albeit less restrictive) than formal credit, suggesting that accessible local micro-credit and insurance schemes would increase the probability of households to resort to external sources, rather than suffering through economic shocks (Giné, 2011).

Second, although leveraging natural resources turns out to be a less common shock response than expected, resources can represent an important safety net locally. Our findings suggest, however, that the concentration of land ownership (especially to the degree observed at sites in Ghana and some Latin American countries) represents an important disincentive to natural resource-based coping. Improving access to natural resources through land reform or the creation of extractive reserves may thus sometimes reduce vulnerability, in addition to providing other benefits.

Apart from these observed village-level covariates, both village- and site-level intercepts of the hierarchical MNL are larger than most household-level covariate coefficients for many sites. Observed and unobserved differences between the units at these higher levels of aggregation thus eventually become more powerful predictors of shock response behavior than household-level covariates.

A few caveats apply. While the use of hierarchical modeling has helped us to uncover potentially relevant village- and site-level behavioral patterns, the overall explanatory power of our model is low. Few of the predicted posterior probabilities closely correspond to stated behavior. Moreover, the violation of IIA under some combinations of predicted and base response categories undermines the value of the model as a predictive tool. While explanatory power may perhaps be improved by inclusion of additional or alternative covariates, this is most likely also a result of the nature of the stated response data. Independent teams of enumerators at the various PEN sites may simply have attached varying levels of importance to the issue of shocks. Subjective accounts of shock severity undoubtedly differ across cultures. It is thus likely that some important shocks have gone unreported for some sites, whereas normal seasonal fluctuations were reported as shocks in others. Effects like this are likely to blur distinctions in underlying behavioral patterns. Finally, from a pure modeling perspective, it would appear that attempting to improve a regression model's performance as a predictive tool by adopting a hierarchical framework may have drawbacks. Solving time was exceedingly long for the multilevel MNL (more than 24 hours in some cases) and convergence was unstable for some combinations of covariates and random effects. And while village-level intercepts are approximately normally distributed, PEN site intercepts were found to be irregularly distributed in the hierarchical MNL. Adding site-level predictors, such as altitude and rainfall patters, may attenuate this phenomenon that most likely results from unobserved, though considerable, heterogeneity across sites.

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Table 1: Shocks and responses in the global PEN data base

Number of responses	Covariate Shocks	Idiosyncratic shocks Labor	Other
Reduced Consumption	655	189	141
Used Wild Products	267	95	49
Asset Depletion	387	538	179
Reallocated Labor	464	277	91
Sought Outside Help	137	283	94
Total	1910	1382	555

Relative distribution	Covariate Shocks	Idiosyncratic shocks Labor	Other
Reduced Consumption	35%	14%	26%
Used Wild Products	10%	5%	5%
Asset Depletion	20%	39%	32%
Reallocated Labor	28%	21%	20%
Sought Outside Help	7%	20%	17%
Total	100%	100%	100%

Table 2: Descriptive statistics of explanatory variables

Variable	Unit	Mean	Std. Err.	Std. Dev.
Household level variables				
Labor shock	binary (0,1)	0.38	0.01	0.48
Covariate shock	binary (0,1)	0.47	0.01	0.50
Other shock	binary (0,1)	0.15	0.01	0.35
Shock severity	binary (1,2= severe)	1.29	0.01	0.45
Household size	number	6.68	0.06	3.32
Female headed	binary (0,1)	0.08	0.00	0.27
Age of household head	years	45.69	0.25	14.08
Education of household head	years	4.03	0.07	4.24
Dependency ratio	share of dependents	1.05	0.02	0.90
Crop land	ha	3.61	0.14	8.05
Asset index	-	-0.19	0.02	1.05
Savings	USD ppp	301.23	33.68	1926.99
Debt	USD ppp	368.99	30.94	1770.46
Distance to forest edge	minutes walking	37.11	0.80	45.86
Environmental income share	Share	0.27	0.00	0.17
Village level variables				
Village land Gini coefficient	-	0.39	0.00	0.14
Formal credit access	number of HHs	64.92	4.25	242.92
Informal credit access	binary (0,1)	0.56	0.01	0.50
Health center in village	binary (0,1)	0.27	0.01	0.44
Distance to agricultural product market	minutes walking	67.57	1.65	94.31
Distance to extractive product market	minutes walking	68.32	1.37	78.52

Table 3: Comparison of results from MNL and MNP models

	Used Wild Products			Asset Depletion			Reallocated Labor			Sought Help		
	Δα (%)	σ	+/-	Δα (%)	σ	+/-	Δα (%)	σ	+/-	Δα (%)	σ	+/-
Shock severity	10		=	-11		=	-14	B	=	-5	B	=
Covariate shock	-18		=	-11	B	=	4		=	-1	B	=
Labor shock	-37		=	-10	B	=	-7	B	=	-7	B	=
Female headed	-17		=	-10		=	-7		=	-10		=
Age of hh	-2		=	-12		=	-10	B	=	-9		=
Education of hh	6	B	=	-6	B	=	-13		=	-1	B	=
Dependency ratio	3		=	-16		=	-5		=	-9		=
Crop land	11	B	=	2		=	-17		=	4	B	=
Distance to forest edge	40		=	-11	B	=	-10		=	-5		=
Asset index	-7	B	=	-11	B	=	-10	B	=	-6	B	=
Savings	55		=	-21	B	=	2	B	=	26		=
Debt	5	P	=	26		=	-36		=	-68		≠
Env. income share	-5	B	=	-22		=	-9	B	=	-8	B	=

Note: The column labeled Δα (%) denotes the percentage difference in the magnitude of the estimated coefficient between the two models. The column labeled σ indicates the statistical significance of the estimated coefficient (where B indicates significance in both models, L indicates significance in the MNL model only, and P indicates significance in the MNP model only). The column labeled +/- denotes whether the signs in the two models are the same (=) or different (≠). To allow for comparison the coefficients of the MNL model were multiplied by 0.625 following Ameniya (1981).

Table 4: A three level random intercept MNL of shock response behavior

	Used wild products			Asset depletion			Reallocated labor			Sought help		
	b		SE	b		SE	b		SE	b		SE
Shock severity	0.19		0.21	0.18		0.16	0.59	***	0.16	0.76	***	0.19
Covariate shock	-0.51		0.27	-1.10	***	0.21	-0.30		0.24	-1.42	***	0.26
Labor shock	0.19		0.29	0.91	***	0.22	0.68	**	0.25	0.74	**	0.26
Female headed	-0.14		0.30	-0.43		0.24	-0.36		0.27	-0.13		0.29
Age of hh	-0.25		0.18	-0.26		0.14	-0.43	**	0.15	-0.28		0.17
Education of hh	-0.35		0.21	-0.11		0.16	0.13		0.17	-0.24		0.20
Dependency ratio	0.09		0.18	0.17		0.14	0.22		0.15	-0.01		0.17
Crop land	-2.20	***	0.59	0.06		0.12	-0.05		0.14	-0.84	*	0.35
Env. income share	0.90	***	0.19	-0.49	***	0.17	0.28		0.17	-0.01		0.20
Asset index	0.42		0.22	-0.04		0.18	0.28		0.19	0.15		0.21
Savings	-0.07		0.34	0.44	*	0.20	-1.32	*	0.53	-0.08		0.32
Debt	-0.51		0.40	0.09		0.15	-0.19		0.21	0.02		0.19
Distance to forest edge	-0.43		0.22	0.07		0.14	-0.02		0.16	0.02		0.17
Formal credit access	-0.81		0.58	0.18		0.15	-0.21		0.22	0.23		0.18
Informal credit access	0.34		0.25	0.78	**	0.22	0.07		0.22	0.62	*	0.25
Health center in village	0.13		0.27	0.16		0.24	0.03		0.25	0.07		0.27
Distance to agric. market	-0.18		0.23	-0.29		0.23	0.04		0.21	0.13		0.22
Distance to extract. market	0.48		0.27	0.61		0.24	0.86	**	0.24	0.35		0.26
Village land gini coeff.	-0.49	*	0.24	-0.07		0.22	-0.11		0.22	0.03		0.24
Constant	-0.88	***	0.18	0.56	***	0.14	0.10		0.15	-0.46	**	0.16
Random effects	*Var*		*Cov*									
Village	0.53		0.14									
Site	1.13		0.29									
Log likelihood	*-2999.17*											
Level 1 units	*2209*											
Level 2 units	*230*											
Level 3 units	*27*											

*** $p \leq 0.001$, ** $p \leq 0.01$, * $p \leq 0.05$

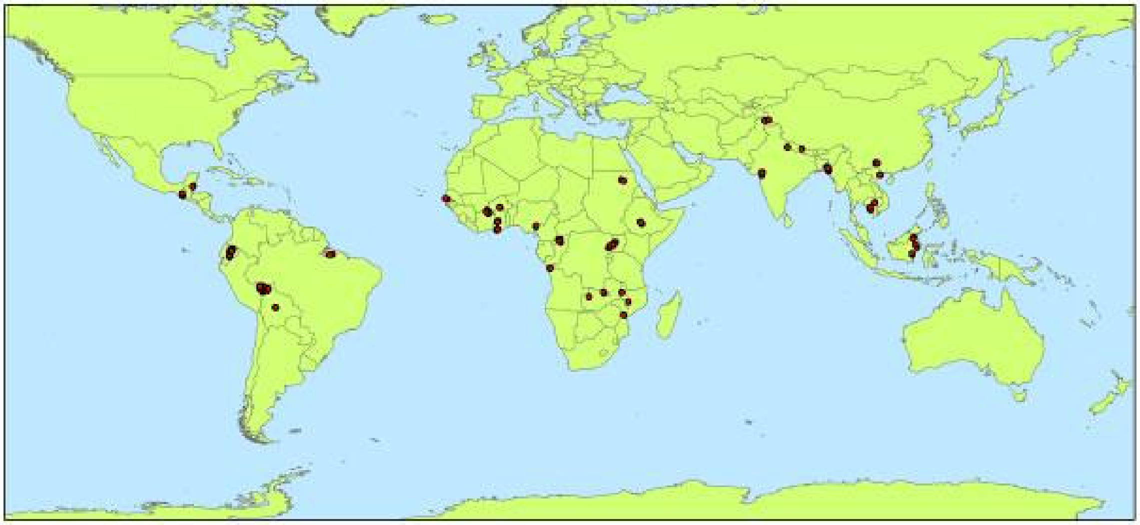

Figure 1: Map of PEN study locations

Note: Some dots represent multiple sites within a country (see text for details).

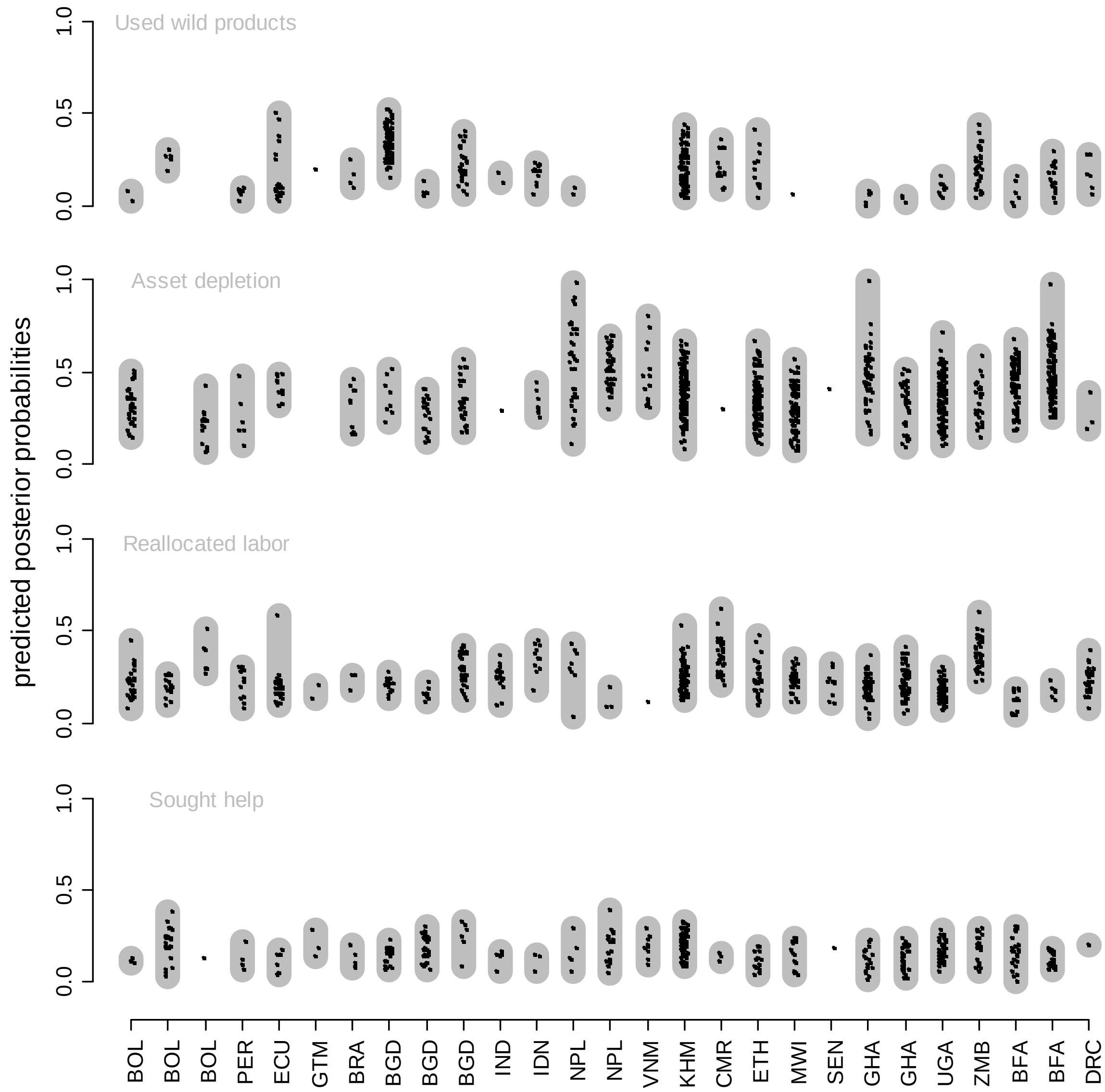

Figure 2: Predicted posterior probabilities (jittered dots) by shock response. Grey areas are for visualization only. Probabilities have to be interpreted vis-à-vis the reduced consumption base category.

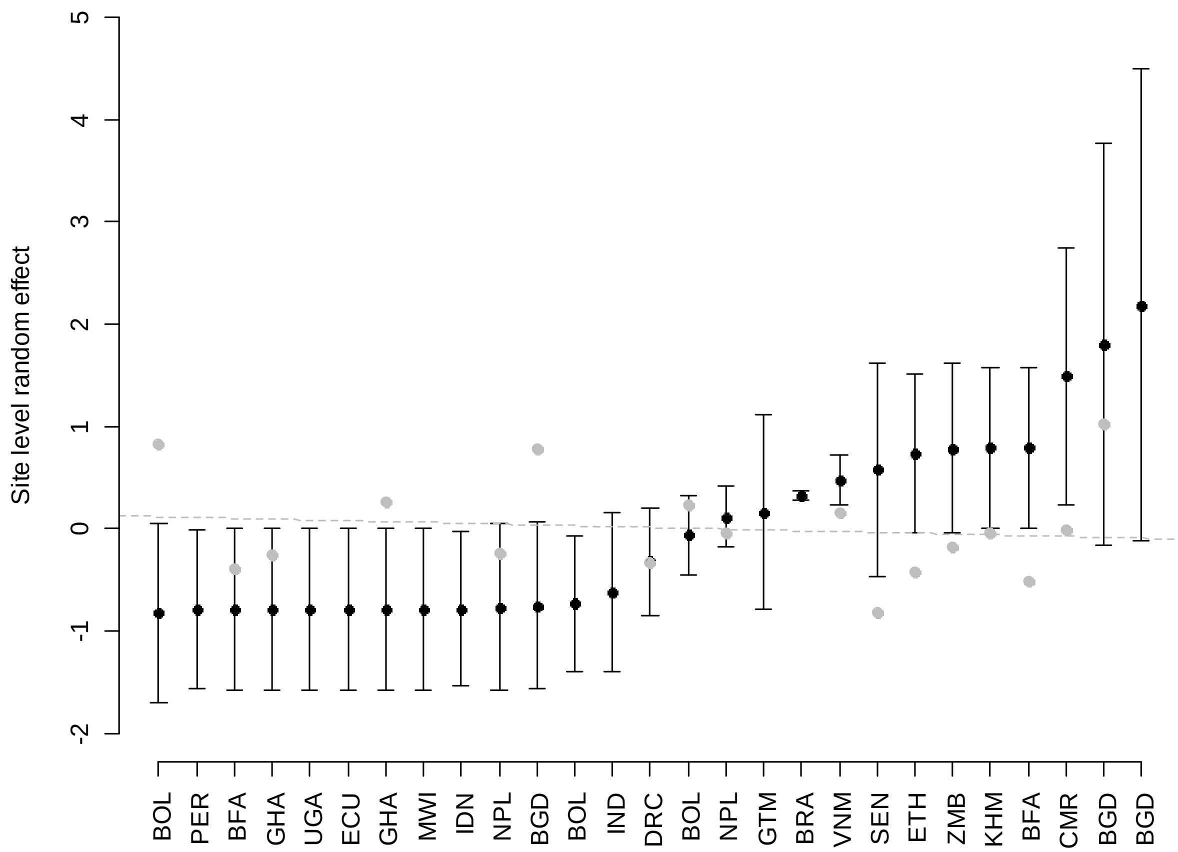

Figure 3: PEN site level intercepts, by country
Note: Each black dot represents a site-specific average random effect; black bars indicate 97.5% confidence intervals. Grey dots and dashed trend line represent rescaled means of annual rainfall.