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Eva Seewald

THE ENVIRONMENT-POVERTY NEXUS USING A MULTIDIMENSIONAL POVERTY INDEX IN RURAL VIETNAMESE HOUSEHOLDS

Contents

Abstract
The environmental-poverty nexus has been subject to research especially in relation to climate change. On the one hand, poor households depend on environmental resources as additional income sources or as additional household products. On the other hand, natural resource extraction further drives climate change. We build on the existing literature using socio-economic panel data from Vietnam to calculate environmental income variables and a multi-dimensional poverty index (MPI). MPIs have been developed to understand poverty in more detail and implement more efficient policies to lift people out of poverty. We use a fixed effects panel logit regression and find that households with higher dependency on environmental income are more likely to be multi-dimensionally poor. Households engaged in extraction activities are larger, less educated and have lower asset values. Natural resource dependence needs to be considered using participatory approaches for successful policies against climate change. Furthermore, structural deprivations such as lack of availability of electricity should be addressed to reduce multidimensional poverty.

Keywords
Natural Resource Dependence – Forest Income – Income Poverty – Multidimensional Poverty – Precipitation Data – Panel Data

Der Zusammenhang zwischen Umwelt und Armut, gemessen durch einen mehrdimensionalen Armutsindex in ländlichen vietnamesischen Haushalten

Kurzfassung

Der Zusammenhang zwischen Umwelt und Armut ist vor allem im Kontext des Klimawandels Gegenstand der Forschung. Einerseits sind arme Haushalte auf Umweltressourcen als zusätzliche Einkommensquellen oder Haushaltsprodukte angewiesen. Andererseits treibt die Entnahme natürlicher Ressourcen den –Klimawandel weiter voran. Wir verwenden sozioökonomische Paneldaten aus Vietnam, um Umwelteinkommen und einen mehrdimensionalen Armutsindex (MPI) zu berechnen. MPIs helfen uns, Armut besser zu verstehen und effizientere Maßnahmen gegen diese zu ergreifen. Wir verwenden eine Logit-Panel-Regression mit festen Effekten. Unsere Ergebnisse zeigen, dass Haushalte mit einer höheren Abhängigkeit von Umwelteinkommen mit größerer Wahrscheinlichkeit mehrdimensional arm sind. Haushalte, die natürliche Ressourcen entnehmen, sind größer, weniger gebildet und besitzen geringere Vermögenswerte. Die Abhängigkeit von natürlichen Ressourcen muss durch partizipatorische Ansätze für eine erfolgreiche Politik gegen den Klimawandel berücksichtigt werden. Des Weiteren sollten strukturelle Benachteiligungen wie die mangelnde Verfügbarkeit von Elektrizität angegangen werden, um mehrdimensionale Armut zu verringern.

Schlüsselwörter

Abhängigkeit von natürlichen Ressourcen – Einkommen aus natürlichen Ressourcen – Einkommensarmut – multidimensionale Armut – Niederschlagsdaten – Paneldaten

1 Introduction

Poverty and climate change are the two main problems that developing countries face, with severe impacts on people's wellbeing. Both problems are linked to the question of resource extraction from the environment. On the one hand, environmental resources support poor households by providing firewood and other non-timber forest products (NTFP) such as herbs and vegetables (Angelsen/Wunder 2003). On the other hand, natural resource extraction degrades forests if not undertaken in a sustainable manner (Birhanu 2014). This increases the damage caused by climate change and prevents further social and economic development (Bretschger 2020). Therefore, natural resource extraction and its impact on poverty has been studied intensively over the past twenty years (Thiry/Alkire/Schleicher 2018; Reddy/Chakravarty 1999; Angelsen/Wunder 2003; Cavendish/Campbell 2008; Jagger 2012; Wunder/Angelsen/Belcher 2014; Bierkamp/Nguyen/Grote 2021). The results show that natural resources can supplement poor households' tight budgets through collecting NTFP. Therefore, natural resource dependence seems to be higher for the poorest households. Additionally, NTFP can also be sold on the market, increasing household income. While poor households are more dependent on NTFP, richer households consume more of them in absolute terms (Cavendish 2000). Natural resource stocks have been reduced due to economic growth in China, Ethiopia, and Vietnam, making research in these countries especially important (Nguyen/Grote/Nguyen 2017; Qin/Liao 2016; UNDP 2014).

The debate about how best to measure poverty is ongoing (Alkire/Santos 2014). Poverty comes with multiple faces. Not only is it defined by a scarcity of monetary values like income or assets but it also comprises other aspects of life such as no access to health services, education, or participation in community activities (Alkire/Foster 2011a). The UN defines poverty as "[...] a denial of choices and opportunities, it is a violation of human dignity. It means lack of basic capacity to participate effectively in society. It means not having enough to feed and clothe a family, not having a school or a clinic to go to, not having the land on which to grow one's food or a job to earn one's living, nor having access to credit. It means insecurity, powerlessness and exclusion of individuals, households and communities. It means susceptibility to violence and it often implies living on marginal and fragile environments, not having access to clean water and sanitation." (United Nations 20.05.1998). To capture these categories in a measure of poverty, researchers have developed multidimensional poverty indices (MPIs).

The impact of natural resource dependence on multidimensional poverty has not been subject to research so far. Because MPIs include aspects such as health and education, they offer different information from poverty measured solely by income, leading to different policy implications and providing deeper insights into the determinants of poverty.

With this analysis we try to close this research gap. To do this, we use a uniquely large socio-economic panel dataset from Vietnam from 2013, 2016, and 2017. This dataset allows us to calculate an MPI based on current UN recommendations and environmental income. The aim of this article is thus: (1) to give an extensive literature review on the topic and (2) to analyze the link between natural resource dependence and the multidimensional poverty of poor rural households in Vietnam.

The results show that dependency on natural resources increases multidimensional poverty. This means it is important to take this dependency into account when policymakers attempt to address both poverty and environmental issues by restricting access to forested or non-forested areas for collection.

The remainder of our paper is structured as follows. In Section 2 we review the existing literature regarding natural resource dependency and poverty. Section 3 describes the study sites and the data and lays out our conceptual framework. Section 4 displays the results, which are then discussed in Section 5. Finally, Section 6 concludes.

2 Literature Review

2.1 Environmental Income and Poverty

Diversified sources of food and income are common among poor rural households. With respect to income, such households not rely solely on agriculture but add available off-farm employment, self-employment and migration opportunities as well as extraction activities to their portfolio (Babulo et al. 2008; Soltani et al. 2012; Salam 2020). Extraction activities take place in forests and non-forest environments. Income generated from these activities is defined as environmental income by Angelsen et al. (2014): *"Environmental income refers to extraction from non-cultivated sources: natural forests, other non-forest wildlands such as grass-, bush- and wetlands, fallows, but also wild plants and animals harvested from croplands"*. Environmental income in absolute terms determines the extraction level whereas relative environmental income measures the dependence of households on natural resource extraction (Nguyen/Do/Grote 2018). According to Babulo et al. (2009), environmental income fulfills three functions: (1) forest products help to maintain the level of consumption for example in pre-harvest seasons, (2) forest products can form safety nets in times of shocks, and (3) selling forest products to increase household income can provide a way out of poverty.

The contribution of environmental income to total household income has been increasingly investigated in the past twenty years (Thiry/Alkire/Schleicher 2018; Reddy/Chakravarty 1999; Angelsen/Wunder 2003; Cavendish/Campbell 2008; Jagger 2012; Wunder/Angelsen/Belcher 2014; Bierkamp/Nguyen/Grote 2021). The results indicate that neglecting environmental income can lead to biased identifications of the poor and, thus, inefficient policy initiatives to alleviate poverty (Sjaastad et al. 2005). The leading data collection project for identifying environmental income is led by CIFOR's Poverty and Environment Network (PEN). A recent study based on this project reports that combined environmental income accounts for 27.5% of total income in Sub-Sahara Africa, Latin America, and Asia (Wunder/Angelsen/Belcher 2014). Of this, 21.1% is derived from natural forests and 6.4% from non-forest environments. Angelsen et al. (2014) conclude that income from forests is highest in Latin America (28.6%), followed by Africa (21.4%) and Asia (20.1%). In comparison, income from non-forest environments was highest in Africa (9.6%). Looking at the composition of environmental income from forests, the most important component is fuel wood (35.2%) while the second most important is food (30.3%). The order is reversed when income from non-forest environments is investigated. A previous meta-analysis comprising 51 case studies from 17 countries identified that forest environmental income accounts for 22% of total income (Vedeld et al. 2007). The researchers point out that neglecting even relatively small contributions of forest income to total income will create serious biases (Vedeld et al. 2007).

Babulo et al. (2009) report that forest environmental income accounts for 27% in Ethiopia, questioning the view that livestock is the second most important source of income in the study area. Evidence from Malawi indicates that forest income accounts for around 15% of total household income (Kamanga/Vedeld/Sjaastad 2009), while this reaches 26% in Uganda (Jagger 2012) and 33% in Zambia (Mulenga/Richardson/Tembo 2012). Covering households from Benin, Heubach et al. (2011) find that the income from NTFP varies among the traditional livelihoods of different ethnic groups. A livelihood strategy analysis from Iran reveals that 64% of households diversify their income sources, while the poorest households use a livelihood strategy that is highly dependent on forest extraction and livestock grazing (Soltani et al. 2012). Results from Southern China and Cambodia find that average environmental income accounts for 31.5% (Hogarth et al. 2012) and 27% (Nguyen et al. 2015) of total income respectively.

That poor households are most dependent on extracting activities reflects the fact that such activities are inferior to other activities and are dropped as alternatives become available (Babulo et al. 2008; Mamo/Sjaastad/Vedeld 2007; Soltani et al. 2012). In the absence of alternative income sources, extracting activities can therefore be seen as a poverty trap (Angelsen/Wunder 2003; Cavendish/Campbell 2008; Appiah et al. 2009). Supporting this, Cavendish/Campbell (2008) and Kamanga/Vedeld/Sjaastad (2009) conclude that environmental income is important for fighting poverty but might not be a way out of poverty. Therefore, better educated households are less dependent on environmental income (Mamo/Sjaastad/Vedeld 2007; Kamanga/Vedeld/Sjaastad 2009; Voelker/Waibel 2010; Mulenga/Richardson/Tembo 2012). Older people extract less because of the arduous nature of these activities (Mamo/Sjaastad/Vedeld 2007; Mcelwee 2008; Mulenga/Richardson/Tembo 2012) and might turn to activities requiring more experience (Cavendish 2000). Households headed by a female are more likely to collect forest products (Babulo et al. 2008), while the opposite is found in Zambia by Mulenga/Richardson/Tembo (2012). Indicating that asset-rich households are less dependent on natural resource extraction, Babulo et al. (2008) and Mulenga/Richardson/Tembo (2012) find that holding larger plots of land decreases the likelihood of engaging in forest extraction activities. This is supported by the findings of Wunder/Angelsen/Belcher (2014), which indicate that asset and income poverty increase dependence on environmental extraction.

In addition to dependence on environmental income, the effect of environmental income on equality measures has been investigated. Angelsen et al. (2014) find that inequality increases by 4.7 percentage points when environmental income is not included in total household income. When accounting for environmental income, the GINI coefficient increases from 0.28 to 0.41 in Ethiopia (Mamo/Sjaastad/Vedeld 2007). Despite these results, environmental income has not been considered in policies yet (Wunder/Angelsen/Belcher 2014). Wunder/Angelsen/Belcher (2014) argue that this might be because extraction activities may be seen as a backward relict and offer little scope for technological progress and policy interventions. This is an especially pressing issue in light of the current measures undertaken to protect forests from degradation. If poorer people’s dependence on environmental products is not taken into account, this can leave them worse off due to restricted access and exclusion from decision-making authorities (Adhikari/Di Falco/Lovett 2004; Reddy/Chakravarty 1999; Sherbinin et al. 2008).

2.2 Environmental Income and Multidimensional Poverty

Traditionally, the analysis of poverty relied on a measurement of income or expenditure, classifying households falling short of a pre-determined threshold as poor. The first and second generation of poverty measurements thus commonly generated static and dynamic information on income poverty (Carter/Barrett 2006). However, the stochastic nature of income, especially in developing countries, has led to the emergence of literature that focuses on the underlying asset structure to determine the expected income of households. This should, in theory, provide a more precise picture of the actual livelihood of households (Carter/Barrett 2006; Amare/Hohfeld 2016). Yet another approach to measuring poverty is that of human poverty, which goes beyond the traditional income-based poverty measures by focusing on actual human living conditions and the deprivations faced by the most vulnerable parts of society (Sen/Anand 1997). Multidimensional poverty indices (MPIs) provide a more detailed picture about patterns of poverty than income-based measures that rely on an assessment of what amount of income *would* normally be sufficient to meet minimum needs (Alkire/Santos 2014).

Despite the vast literature regarding the nexus of income poverty and environmental income, studies investigating the effect of environmental income on multidimensional poverty are scarce (Thiry/Alkire/Schleicher 2018). Evidence from Pakistan solely states that 95% of the sample households use wood for cooking and, thus, are dependent on natural resources. However, only 55% of the households in the sample can be considered multidimensionally poor (Khan/Saqib/Hafidi 2021). Therefore, there is demand for a deeper analysis of the connection between environmental resource dependence and multidimensional poverty.

3 Data and Conceptual Framework

3.1 Thailand Vietnam Socioeconomic Panel Data

The household data used to construct the MPI and environmental income come from the Thailand Vietnam Socioeconomic Panel (TVSEP) project (www.tvsep.de). Data collection was conducted under the auspices of the research project “Poverty dynamics and sustainable development: A long-term panel project in Thailand and Vietnam, 2015-2024”. Building on previous work by the research unit FOR 756 of the Deutsche Forschungsgemeinschaft (DFG), this project aims at providing a long-term panel.

The TVSEP project collects data on 4,400 households, 2,200 households in each country. The study sites in Vietnam cover the rural provinces of Dak Lak, Ha Tinh, and Thua Thien Hue (Figure 1). The sampling of the provinces ensures a representative sample of the rural population and was undertaken in three steps (Hardeweg/Klasen/Waibel 2013). First, as the aim of the project is to study poverty and development, provinces were selected based on poverty indicators such as low average per capita income. Taking into account inter-district diversity regarding agro-ecological zones, a stratification strategy was applied. Second, two villages per sub-district were selected by considering the probability proportional to the population of the respective sub-district. Third, ten households were chosen from each village. Data collection comprises household questionnaires as well as village head questionnaires to capture village characteristics (e.g. infrastructure, economic, and environmental status). The household questionnaire contains information on socio-demographic characteristics, income sources, financial situation, and holdings of land and assets. There is a section exclusively collecting information on extracting activities. Attrition has been kept well below 5% (Parvathi et al. 2019).

The household data in our analyses rely on data from 2013, 2016, and 2017 comprising 4,383 households. All monetary values have been converted to 2005 PPP USD.

3.2 Environmental Income

To calculate environmental income, we use the section on collecting, hunting, and logging of the TVSEP project's questionnaires. Households are asked what they extract, how often they extract these forest products, and whether they have to pay to access the sites. Households are also asked to estimate the amount for which they could sell those products using farm gate prices. In accordance with the literature, we use gross environmental income as labor markets are limited in the study areas (Babulo et al. 2009).

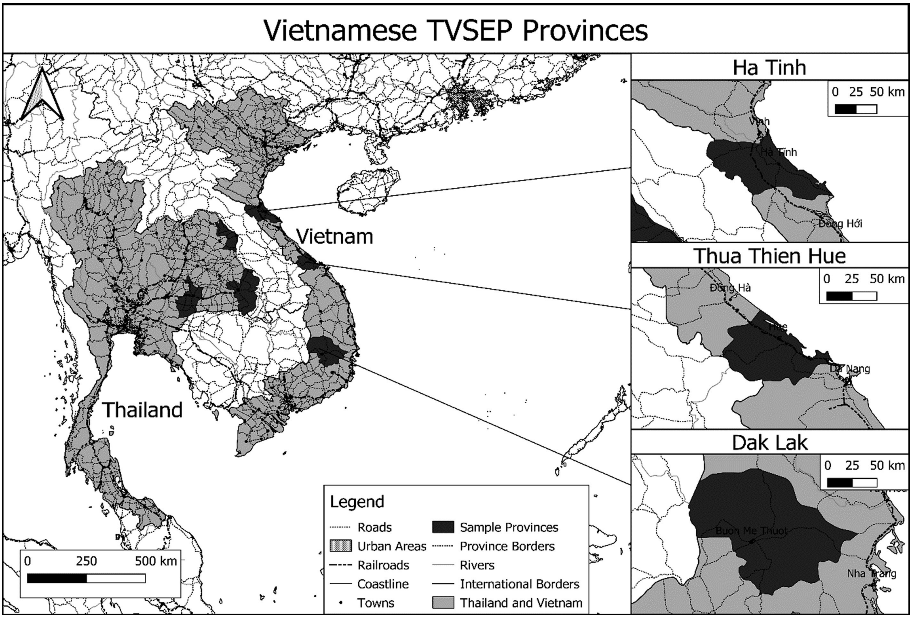

Figure 1: Map of the Vietnamese Provinces Covered by the TVSEP Project / Source: the authors using QGIS)

3.3 Income Poverty and Multidimensional Poverty

We construct a locally adapted multidimensional poverty index for our sample households by selecting the appropriate dimensions and indicators. The multidimensional poverty index can be adapted in its dimensions, indicators, and weights to account for local conditions and research foci (Ayuya et al. 2015; Ogutu/Qaim 2019; Oshio/Kan 2014). Aguilar/Sumner (2020) provide an overview of the most commonly used MPIs. We draw on this wide variety and opt for four dimensions of multidimensional poverty: health, education, standard of living/basic infrastructure, and monetary poverty. With the available TVSEP data, we could replicate the World Bank index. Our index differs from the original measures in three aspects: we dropped the child mortality indicator due to data unavailability, added the income indicator, and replaced the floor indicator with a housing indicator as in UNDP/ OPHI (2019).

Following the selection of dimensions and indicators, we define the cutoff vector *z* that contains information on the cutoff below which a household is considered deprived in the respective dimension, and the weight vector *w* for the weighting of each dimension (Alkire/Foster 2011b). In line with common practice, we assign the same weight to all dimensions, and indicators are weighted equally within dimensions (Figure 2). We construct a column vector *d* of the deprivation counts, which is simply the sum of the weighted values of experienced deprivations (Alkire/Foster 2011b). Lastly, we define a poverty cutoff *k* (with $0 < k \leq d$) that classifies a household as poor if their deprivation count lies on or above *k* (Alkire/Foster 2011b). This procedure is referred to as the dual-cutoff method (Alkire/Foster 2011a, 2011b). We define households as poor if they are deprived in indicators whose combined weights add up to $k \geq 0.25$. This is a lower threshold than those of other common indices (0.33) but sticks to the practice of defining households as poor when they are deprived in indicators whose weights are equivalent to that of an entire dimension.

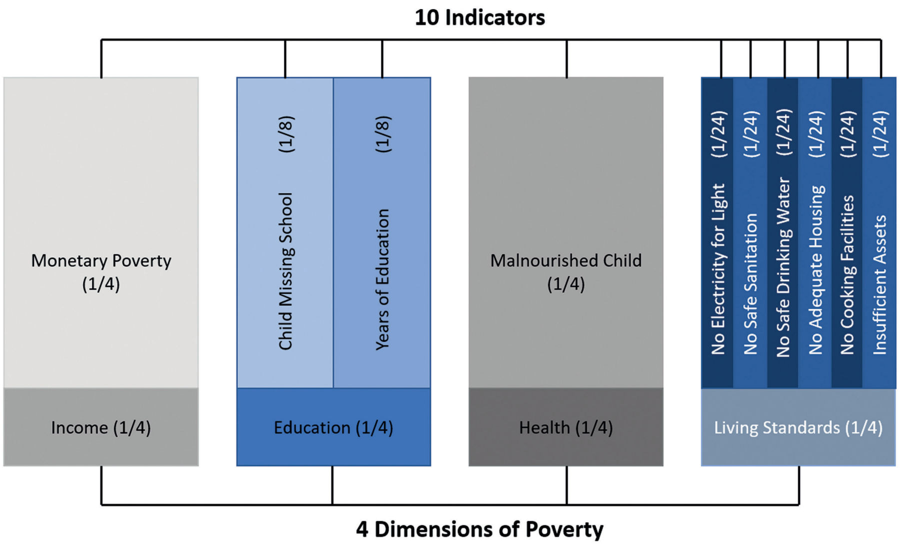

Figure 2: Dimensions and Indicators of the Multidimensional Poverty Index / Source: the author adapted from UNDP/OPHI (2019)

3.4 Specification of Econometric Model

We use a logit fixed effects panel regression to determine the effect of environmental income on the MPI, using the cut-off value of 0.25. The independent variables of interest are environmental income, denoted by $Env.Income_{it}$ in equation [1], and the share of environmental income in total household income, denoted by $Dependence_{it}$. Further control variables consist of a vector of socio-demographic characteristics, θ_{it}, including age, gender, and ethnicity of the household head, average education, household size, and dependency ratio. Furthermore, we add a vector of economic information, ρ_{it}, namely the logarithm of the value of assets, a dummy indicating whether a household is involved in non-farm self-employment, and the logarithm of land area for farming. Index I denotes the household and t the year. After running the regression, average marginal effects are calculated to make interpretation possible. The regression is run for each country separately.

$$MPI_{it} = \beta_0 + \beta_1 Env.Income_{it} + \beta_2 Dependence_{it} + \beta_3 \theta_{it} + \beta_4 \rho_{it} + \epsilon_{it} \quad [1]$$

4 Results

4.1 Description of the Sample

Table 1 provides an overview of the socio-demographic and economic characteristics of the sample. It also shows characteristics of households involved in extracting activities (extracting households) and those who are not (non-extracting households). The Wilcoxon rank and χ^2-tests show whether the differences between these groups are statistically significant. We see that most of the differences are statistically significant, except the gender of the household head. On average, households comprise 3.84 members while the household size is larger for extracting households than for non-extracting households. Household heads are younger in extracting households than in non-extracting households, which is in line with the literature that suggests that younger households are more likely to be involved in extracting activities (Mamo/Sjaastad/Vedeld 2007; Mcelwee 2008; Kamanga/Vedeld/Sjaastad 2009). Also in accordance with existing literature, extracting households are on average less educated than non-extracting households and are more likely to belong to a minority group (Mamo/Sjaastad/Vedeld 2007; Voelker/Waibel 2010). Examining economic characteristics, in line with existing literature, shows that extracting households have lower total annual incomes, lower values of assets, and are less likely to be self-employed. However, they are more likely to own a tractor. Average environmental income in the whole sample is 330 2005 PPP USD representing 3.7% of total household income. For extracting households, it accounts for 9.7% of total household income and reaches on average 873.37 2005 PPP USD. A difference worth mentioning is that extracting households own more land than non-extracting households. However, the amount of land owned is generally small in Vietnam. In addition, we checked for multicollinearity using the variance inflation factor. All factors were below the threshold of 5, multicollinearity is not an issue for the analysis.

	Whole sample	**Extracting**	**Non-extracting**	**T-Test**
Socio-demographic characteristics				
Household size	3.84 (1.71)	4.27 (1.77)	3.58 (1.62)	-14.36[a] ***
Dependency ratio	0.32 (0.3)	0.31 (0.26)	0.32 (0.32)	-1.08[a]
Age of household head	54.91 (12.92)	52.2 (12.95)	56.56 (12.61)	12.28[a] ***
Average education	8.25 (2.87)	7.32 (2.75)	8.83 (2.79)	17.55[a] ***
Ethnicity of household head (1 = minority)	0.21 (0.41)	0.46 (0.5)	0.07 (0.25)	1,200[b] ***
Gender of household head (1 = female)	0.2 (0.4)	0.19 (0.39)	0.21 (0.41)	2.15[b]
Economic characteristics				
Total annual household income	8,777(13,024)	6,829 (12,981)	9,961 (12,909)	12.81[a]***
Asset value	2,683(4,840.09)	2,093.77 (4,462)	3,041 (5,023)	10.71[a]***
Land size owned	0.94 (2.35)	1.23 (2,82)	0.77 (1.99)	-13.0[a]***
Tractor (1 = yes)	0.24 (0.43)	0.26 (0.44)	0.23 (0.42)	4.58[b]**
Non-farm self-employment (1 = yes)	0.29 (0.45)	0.18 (0.39)	0.35 (0.48)	176.61[b]***
Extracting (1 = yes)	0.38 (0.48)	1	0	5600.00[b]***
Environmental income	330 (6,861)	873(11,139)	0	-68.05[a]***
Relative environmental income (%)	0.037 (0.24)	0.097 (0.38)	0	-65.72[a]***
No. of observations	5,570	2,106	3,464	

Standard deviations in parentheses; monetary values converted to 2005 PPP USD,
[a] Wilcoxon rank sum test
[b] X^2-test
* p<0.1, ** p<0.05, *** p<0.01.

Table 1: Socio-demographic and economic characteristics by extraction status / Source: author's calculation

4.2 Multidimensional Poverty

In Figure 3 we present the contribution of the dimensions to overall poverty, the incidence, intensity, and adjusted headcount ratio of multidimensional poverty. The incidence of multidimensional poverty is calculated as the percentage of households that have been identified as poor. The intensity of multidimensional poverty is calculated as the average share of weighted deprivations faced by households identified as poor. The adjusted headcount ratio is obtained as the "sum of the weighted deprivations that the poor experience, divided by the total population" (Alkire/Santos 2014). To understand the patterns of poverty in Vietnam, we present a decomposition by indicators. We can recognize some general trends. Both the incidence and adjusted headcount ratio decrease over time, reflecting the rather successful development progress (World Bank 2020; Ravallion 2010). However, the intensity of poverty has not decreased at the same pace. Thus, households that remained poor were not able to decrease the number of dimensions in which they were deprived. The decrease in the adjusted headcount ratio is largely driven by households escaping poverty. Regarding dimensional decomposition, it is apparent that monetary poverty makes the largest contribution to overall poverty with minor fluctuations between years. Over time, the contribution of child malnutrition has increased. The significant reduction in the incidence and adjusted headcount ratio seem to be attributable to the improvement in living standards, while problems in monetary poverty, education, and health persist.

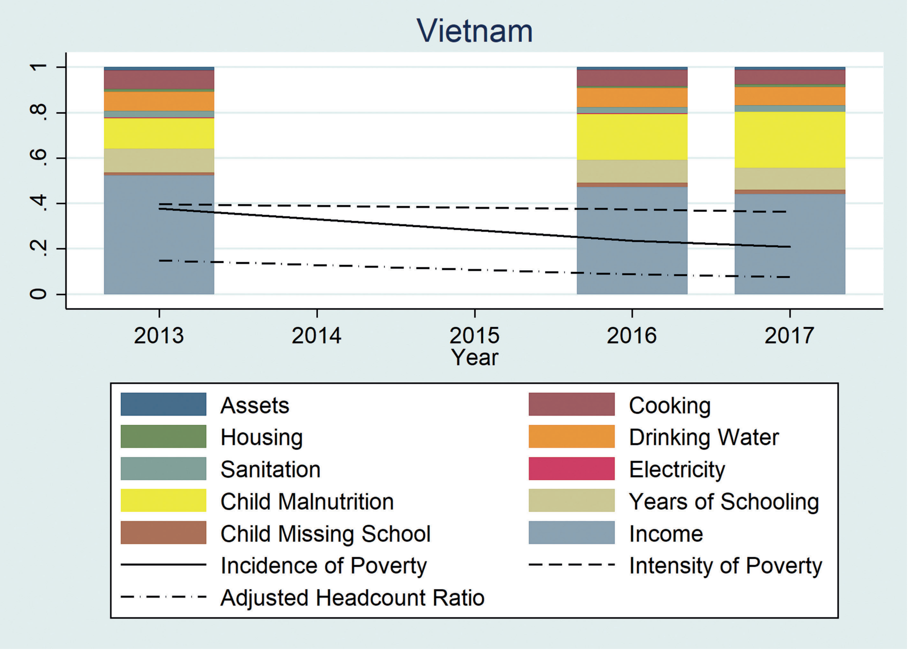

Figure 3: Contribution of Indicators to Multidimensional Poverty, Incidence, Intensity, and Adjusted Headcount Ratio of Multidimensional Poverty / Source: the author's depiction

Looking at the MPI by extracting status in Table 2 we see that extracting households are more likely to be multidimensionally poor than non-extracting households. Although poverty decreased generally between 2013 and 2016, it is higher in households engaged in extraction.

MPI (0.25 cut-off)	Whole-sample	Extracting	Non-extracting
2013	0.377	0.477	0.3
2016	0.235	0.38	0.168
2017	0.209	0.325	0.139

Table 2: MPI deprived in 2013, 2016, and 2017 by extraction status / Source: author's calculation

4.3 Econometric Results

Table 3 displays the results for the logit fixed effects panel regression as introduced in Section 3.4. The results show that larger households are 7.1% more likely to be poor, while being better educated decreases the likelihood of being poor by 2.4%. The age of the household head does not affect the likelihood of being poor. Higher values of assets and larger landholdings significantly decrease the likelihood of being poor. Most importantly, the results show a significant effect for environmental income and relative environmental income. While environmental income significantly decreases the likelihood of being poor, its effect is negligible. Relative environmental income, on the contrary, increases the likelihood of being poor, agreeing with the literature that suggests that households more dependent on environmental income tend to be poorer (Babulo et al. 2008; Mamo/Sjaastad/Vedeld 2007; Soltani et al. 2012).

	MPI
Household size	0.071***
	(0.028)
Dependency ratio	0.137
	(0.091)
Age of household head	-0.001
	(0.002)
Average education	-0.024***
	(0.009)
Ethnicity of household head (1 = minority)	0.092
	(0.133)

	MPI
Gender of household head (1 = female)	-0.008
	(0.053)
Asset value (in logs)	-0.051***
	(0.016)
Land size for farming (in logs)	-0.036*
	(0.018)
Non-farm self-employment (1 = yes)	-0.036
	(0.033)
Environmental income	-0.00004**
	(0.00002)
Relative environmental income (%)	0.104*
	(0.064)
No. of observations	1,527
LR $chi^2(11)$	132.51
Prob. > chi^2	0.000

Standard errors in parentheses; monetary values converted to 2005 PPP USD,
* p<0.1, ** p<0.05, *** p<0.01.

Table 3: Results of the fixed effects logit panel regression on the determinants of multidimensional poverty / Source: author's calculation

5 Discussion

Comparing the results from Section 4 to the insights from the literature review in Section 2, we can say that they are mainly in line with the existing literature. Households engaged in extracting activities are significantly different from households that are not engaged in extraction activities. They show lower education levels, are younger, have more members, are more likely to belong to a minority, and are poorer. All these differences are in line with the determinants of environmental income discussed in Section 2. Not in line with these findings, however, is that extracting households are less likely to have female heads. This can be explained by the fact that men extract more in Asian countries, as found in an analysis by Sunderland et al. (2014). In addition, the larger landholdings of extracting households were also identified by Mcelwee (2008) in Ha Tinh, which is also part of the TVSEP project.

It seems that multidimensional poverty and environmental income are interlinked in the same way as income poverty and environmental income. We see that poorer households are more likely to be engaged in extracting activities and that poorer households are more dependent on environmental income. This is in line with the findings from Babulo et al. (2008) and Soltani et al. (2012), among others. Environmental and relative environmental income statistically significantly affect poverty. However, the effect of environmental income is close to zero, indicating that economically it might not help households to move out of poverty. This is supported by the fact that households with a higher relative environmental income and, therefore, a higher dependency on environmental income, are more likely to be poor. This supports the literature mentioned in Section 2 (Babulo et al. 2008; Mamo/Sjaastad/Vedeld 2007; Soltani et al. 2012). Our interpretation of the results is supported by Dasgupta et al. (2005) stating that there is little evidence of a significant connection between poverty and environmental income in Vietnam. However, they also conclude that these are highest in steeply sloped areas in the northern and western highlands inhabited by ethnic minorities (Dasgupta et al. 2005). Those regions are included in the TVSEP provinces, e.g. the province of Ha Tinh, and can explain the findings in Table 3.

As the multidimensional poverty index addresses several categories mentioned in the UN's definition of poverty (United Nations 20.05.1998) which are also represented in SDG 1 (Feliciano 2019), the analysis of its determinants can give us some new insights on how to alleviate poverty (Alkire/Santos 2014). The results of Section 4 emphasize the importance of taking the dependence of poor households on environmental products into account when introducing new policies, particularly regarding the protection of the environment in the context of action against climate change (Adhikari/Di Falco/Lovett 2004; Reddy/Chakravarty 1999; Sherbinin et al. 2008).

Although our analysis gives a promising picture of the effect of environmental income on multidimensional poverty, it can at the same time be seen as a starting point, as this is the first analysis investigating the connection of these two variables. Therefore, the analysis has several limitations which need to be addressed in further analyses. First, reverse correlation may play a role, as indicated by the fact that poor households extract environmental products as a coping strategy so that, thus, being poor affects the level of extraction as well. Second, using relative environmental income might not be a good proxy of the dependence of households on extraction (Nerfa/Rhemtulla/Zerriffi 2020). Nerfa/Rhemtulla/Zerriffi (2020) argue that this approach is less suitable for circumstances when forest and non-forest products are mainly collected for households' own consumption than, for example, time spent collecting.

6 Conclusion

This analysis is the first to attempt to investigate the poverty-environmental dependence nexus using a multidimensional poverty index instead of relying on income poverty. In order to investigate this connection, we use a uniquely large panel dataset from Vietnam. This data allows the calculation of an adjusted MPI in accordance with the literature and environmental income on household level. Tests for revealing statistically significant differences between samples are applied to investigate whether extracting households are different from non-extracting households. To determine the effect on MPI, a fixed effects panel logit regression is used. The results show that extracting households are significantly different to non-extracting households. They are poorer, younger, less educated, and are more likely to belong to an ethnic minority. However, only for Vietnam, environmental income is statistically significantly different from zero. The regression results reveal that the likelihood of being poor increases when dependence on environmental income is higher. Therefore, policymakers should take the dependence of poor households in the highlands into account. Policies which do not incorporate this dependence might not be successful, especially when it comes to implementing environmental protection policies restricting access for collecting activities. Policies should thus be developed using a participatory approach such that households dependent on natural resource extraction can be part of the decision-making process. Furthermore, policymakers should focus on investing in infrastructure such as sanitation and electricity or in education about diverse diets to fight children's malnutrition in order to reduce multidimensional poverty. Further research, nevertheless, is needed to address the reverse causality issue arising through the intertwining of poverty and environmental income. In addition, a better measure for dependence on extracting activities, as suggested by Nerfa/Rhemtulla/Zerriffi (2020), should also be applied to get a better estimate of dependence.

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