Spatially heterogeneous effects of collective action on environmental dependence in the Kavango-Zambezi Transfrontier Conservation Area

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Title

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Abstract

Many poor rural households depend on products from non-cultivated environments for subsistence and commercialization. Collective action schemes, such as community conservancies aim at maintaining natural resource quality and thus potentially contribute to the sustainability of environmental income sources. Little is known about whether and under which contextual conditions these schemes effectively promote environmental income generation. Advances in remote sensing and improved access to spatial datasets improve our ability to study how local contextual heterogeneity determines whether and how much rural households depend on the environment. Here we quantify environmental income and dependency based on original farm-household data collected in Namibia's share of the Kavango-Zambezi Transfrontier Conservation Area. We then estimate the effect of collective action on environmental income and dependency in a quasi-experimental regression-based approach that controls for historical determinants of community-based natural resource management schemes and explores contextual variation in exposure to tourism activity. Results suggest that collective action schemes tend to foster livelihood strategies that are, on average, more dependent on the environment. However, this effect is driven by outcomes of households that live in close proximity to touristic enterprises, where such livelihood strategies align better with other income generating opportunities than in areas where agriculture represents the only viable economic alternative.

1. Introduction

Besides crop and livestock farming, many low-income households (HH) in rural areas depend on products from non-cultivated environments for both subsistence and commercial uses. The relationship of rural HH wealth and environmental quality is characterized by complex synergies and trade-offs (Lee and Barrett 2001), where environment-development trade-offs can lead to degradation of natural resources (Barbier 2010). This degradation is especially problematic as Cavendish (2000) finds that environmental income (often unaccounted for) contributes with a substantial share to total income, especially among poorer rural HH. In low- and middle income countries, about a quarter of total income of households in humid and dry forest zones is generated from environmental resources (Angelsen et al. 2014). Using census data from a larger number of low-income countries, Lange, Wodon, and Carey (2018) estimate that, on average, natural capital contributes 14 percent[1] to household income. Accounting for environmental income favorably affects measures of income inequality as shown by Vedeld et al. (2007) and Nguyen et al. (2015). According to Angelsen and Dokken (2015), one reason is that poorer HH consume more environmental products than relatively richer ones.

Two comparative studies of Angelsen et al. (2014) and Babigumira et al. (2014) identify robust correlations of how people engage with their environment on a global scale, including household characteristics, assets, shocks, institutions and location. Case studies by Jiao et al. (2019), Kamanga, Vedeld, and Sjaastad (2009), Kyando et al. (2019), Ofoegbu et al. (2017) and Walelign and Jiao (2017) explore the role of socio-economic covariates such as gender, HH size, wealth level, education, ethnicity and age. Apart from distance to protected areas, these studies do typically not control for potential spatial determinants of environmental income. Exceptions are Ojeda Luna et al. (2020) and Nguyen et al. (2015) who control for

[1] Own calculations based on Lange, Wodon, and Carey (2018, 233) comprising timber and non-timber forest products and protected area net-present values, excluding cropland, pastureland and subsoil assets.

deforestation rates (at landscape level) and road quality, using HH-level survey data. Important research gaps in this literature thus include (i) a lack counterfactual-based studies identifying underlying causal determinants of environmental or forest income and (ii) the integration of observational HH-level survey data with existing spatially explicit data on contextual income determinants, including remote-sensing derived indicators of resource availability and access to markets and public services.

This study seeks to address these gaps by evaluating the effect of local collective action in Namibia's community-based natural resource management (CBNRM) schemes, including the control for observed historical determinants of CBNRM initiatives. CBNRM can solve commons dilemmas by establishing and enforcing resource use and access rights as key mechanisms behind conservation and development impacts (Gibson, Williams, and Ostrom 2005). However, CBNRM schemes have been evaluated with mixed results in both socio-economic and environmental outcome dimensions (Matta and Alavalapati 2006; Meyer et al. 2021; Pailler et al. 2015), while few studies have so far relied on a counterfactual based empirical design (Persha, Agrawal, and Chhatre 2011). Angelsen et al. (2014) and Walelign and Jiao (2017) control for collective action initiatives but, contrary to Persha, Agrawal, and Chhatre (2011), find no global average effect on environmental income. More attention thus needs to be paid to potentially heterogeneous effects across national and subnational spatial scales.

Here we address impact heterogeneity by controlling for spatially explicit determinants of environmental income and dependency, using remote-sensing derived proxies for rural development and natural resource availability. We focus on the role of spatially heterogeneous conservation benefits derived from tourism income opportunities and explore the effectiveness of CBNRM in solving commons problems of natural resource access and use (Bodin 2017; Ostrom 2010) using a quasi-experimental empirical design.

Our regional focus lies on Namibia as the birthplace of communal conservancies, a form of collective action initiative, which were established throughout the country since 1996 (Republic Of Namibia 1996). Conservancies have become an integral part in managing wildlife and fostering socio-economic development, covering over 50% of state-owned land and hosting 225,000 people (http://www.nacso.org.na/). Both outcomes were evaluated, indicating positive impacts (Meyer et al. 2021; Bandyopadhyay et al. 2004). Our study area, Namibia's Zambezi Region, is of global relevance due to its location at the center of the world's second largest Transfrontier Conservation Area (Kavango Zambezi – KAZA TFCA) and variation in potentially relevant spatial determinants of HH environmental income and dependency.

The paper is structured as follows: We first provide a theoretical background on environmental income and dependency, including the related academic debate on human-environment relationships and the factors that moderate this relationship in rural areas (Section 2). We then document the data and empirical approach used to explore our theoretical expectations (Sections 3 & 4). Results and their policy implications are displayed and critically discussed thereafter (Sections 5 & 6).

2. Rural livelihoods and environmental income

The environment provides natural resources, which we conceptualize as natural capital (Sjaastad et al. 2005) with stock-dependent income flows. The stock of natural resources provides environmental products through ecosystem services, which HH benefit from. The utilization of rival products implies some form of interference by the HH, which we term as consumption or commercialization, depending on subsistence or market-oriented use, respectively. As environmental products are usually common goods, they are subject to rivalry and therefore scarce. Options to substitute for environmental product consumption and commercialization are often either limited or absent, leading to overuse in many populated rural areas (Barbier 2010).

Environmental products are characterized as non-cultivated and serve as fuel, food, fiber or fodder (Vedeld et al. 2007). Many of these products are predominantly used for subsistence consumption and have thus been called *hidden harvest* due to their absence on local and global markets (Campbell and Luckert 2002). This aspect makes quantification of environmental income inherently more challenging. Additionally, there is a multitude of concepts that uses forest and environment, as well as income and dependence to describe economic human-nature relations (Angelsen et al. 2012; Das 2010; Mamo, Sjaastad, and Vedeld 2007; Nerfa, Rhemtulla, and Zerriffi 2020; Vedeld et al. 2007; Wunder et al. 2014). Scholars use several terms interchangeably and inconsistently, such as forest income, forest dependency, environmental income, environmental dependency and forest environmental income. Henceforth we use environmental income to refer to the absolute income from environmental product consumption or commercialization and rely on the share of environmental in total income as a measure of environmental dependence.

2.1 Determinants of environmental income

Conceptually, environmental income is jointly determined by the supply of and the demand for environmental products. Environmental supply side determinants represent factors of production (López 1994), i.e. renewable but exhaustible stock resources including soils, freshwater and plant or animal populations to be harvested and hunted (Perman 2011). Additionally, pollution of resources, i.e. the depletion of quality and quantity through environmental degradation by both environmental and anthropogenic factors causes disturbances in the supply of environmental products and services (Haberl et al. 2007).

A critical aspect in determining environmental income of rural HH is their resource endowment, serving as a supply-side proxy. Poor HH are subject to a multitude of constraints including land and assets. HH tend to increasingly rely on environmental products when land for agricultural production becomes scarcer (Angelsen et al. 2012). Correspondingly, Finan, Sadoulet, and Janvry (2005) and Deininger, Jin, and Nagarajan (2009) find that poverty decreases with an increase in land endowment. Meanwhile, asset- and income poor rural HH rely more on environmental resources for their income than the relatively better off (Angelsen et al. 2014; Cavendish 2000).

Soil quality, or soil organic carbon (SOC) as a proxy, and conservation thereof is a causally relevant factor for increasing HH farm income (Bravo-Ureta et al. 2006). These implications for livelihood strategy choices suggest that soil quality directs HH towards agriculture as income source, therefore drawing HH away from the environment. All else equal, we expect that higher levels of SOC correlate with lower levels of environmental income, especially in areas where alternative income opportunities, such as from tourism are absent.

Demand side factors co-determine the choice, consumption, and commercialization quantities of environmental products by households. As mentioned above, environmental dependency is often observed to be higher among comparatively poorer HH. Prior studies identify a variety of related HH-level characteristics, such as family size, age, gender, and education levels as predictors of environmental income (Angelsen et al. 2014; Cavendish 2000; Kamanga et al. 2009; Vedeld et al. 2007). And yet, findings vary across study sites in terms of both direction and magnitude.

Importantly, income shocks affect both absolute environmental income and dependency (Wunder et al. 2014). Temporal increases in demand for environmental products, for example, can be the result of coping strategies adopted by poor households (Angelsen and Dokken 2018). Therefore, environmental products can help poor people in times of need, but potential poverty traps loom when overreliance causes a vicious circle of environmental degradation (Barbier 2010).

Besides HH specific characteristics, local context factors can have an effect on environmental dependency. This is evident for market access, which can reduce environmental product demand by offering alternative livelihood strategies (Nielsen, Ø. J. et al. 2013). We expect HH with a high degree of market integration and well developed market access to be less dependent on environmental products, because HH can generate higher off-farm income from formal employment and businesses as shown by Belcher, Achdiawan, and Dewi (2015).

We also expect market integration to be important with respect to wildlife tourism, to which some CBNRM schemes are exposed (Yergeau 2020). This important industry in African economies encompasses consumptive and non-consumptive tourism ventures (Naidoo et al. 2016). Formally employed HH members can be seen as integrated into the market, yet integration does not necessarily correlate with physical market integration as such (e.g. travel time to local or regional markets) because wildlife presence is subject to different spatial dynamics (Brennan et al. 2020). Direct income from employment in tourism plays a minor role in our study area (Kalvelage, Revilla Diez, and Bollig 2020). However, rural livelihood strategies may still be altered in regions with tourism activity via indirect channels such as informal service provision and commercialization opportunities or redistribution of fees from consumptive tourism.

So far, we find little consideration of spatially explicit proxies for supply and demand side determinants of environmental income in the literature. Recent studies by Watmough et al. (2019) and Yeh et al. (2020) show that remote sensing data can considerably improve predictions of general rural wealth indicators. Watmough et al. (2019) also show that the amount of bare agricultural land surrounding a HH is associated with the poorest HH. Pritchard et al. (2019), however, find no correlation between environmental income or dependency and HH's woody resource availability, which they measure at the village level. Different measurement levels and data generation processes may lead to seemingly contradicting findings especially in global studies, which warrants further research into identifying the role of contextual variation at regional scale.

Spatially explicit secondary data, such as nightlight density can also help to control for regional variation in economic activity and rural development (Jean et al. 2016; Chen and Nordhaus 2011). Given the above-mentioned relationship between wealth and environmental dependence, we expect nightlight levels to negatively correlate with environmental income.

2.2 The role of collective action

Self-organized collective action to overcome the commons dilemma has often been shown to provide for improved provision of environmental products and services when rural communities formulate and effectively enforce rules for natural resource access and use (Bodin 2017; Ostrom 2010). This has led some governments to condition the partial devolution of land property rights to local communities on established CBNRM criteria (Measham and Lumbasi 2013; DRESSLER et al. 2010), especially in southern Africa (Whande, Kepe, and Murphre 2003). Formal CBNRM rules may sometimes replace informal traditional land rights systems, which are often based on agriculture, especially in Namibia (Bollig and Vehrs 2021). Motivation to apply for CBNRM status, i.e. implementing transfers of land use rights, may thus vary across local economic contexts, with nature conservation objectives being dominant only when they synergistically align with economic interests at private and community-level.

The effect of CBNRM on general indicators of welfare has been investigated in various studies indicating positive outcomes (Riehl, Zerriffi, and Naidoo 2015; Suich 2013; Pailler et al. 2015; Bandyopadhyay, Guzman, and Lendelvo 2010). Also Angelsen et al. (2014) and Bandyopadhyay, Guzman, and Lendelvo (2010) find a positive effect of membership in forest user groups and conservancies on *total* household income, but no measurable effect on environmental dependency. Based on our conjecture above, heterogeneous effects of state-promoted CBNRM initiatives on environmental dependence my mask the underlying effects of collective resource management on local livelihood strategies. While more secure property rights may support environmental income generating activities that align with wildlife conservation goals in tourism zones, we expect agriculture-based livelihood strategies (including extensive cattle grazing systems) to rather conflict with environmental income sourcing strategies in zones without tourism activity.

Another open question in research on collective action concerns the conditions, and related social processes, under which individuals and households collaborate towards common goals (Adger 2003; Hamilton and Lubell 2019). Social capital, i.e. the structures and linkages within and between groups, including social networks and trust, are considered both as a driver and a potential outcome of collective action dynamics (Bodin 2017). If it is true that state-promoted CBNRM initiatives are established not exclusively to address local commons dilemmas, we expect that levels of social capital remain unaffected by the contextual factors that we hypothesized to moderate livelihood choices.

3. Study area and data base

The Zambezi Region in north-eastern Namibia, consists mainly of the Northern Kalahari woodland biome and to a lesser extent of the North East rivers ecosystem zone that includes floodplains (Mendelsohn, Robets, and Hines 1997). The region covers 14,785 km² and is surrounded by the rivers Zambezi in the north east, the Chobe in the South East, the Linyanti in the South and the Kwando in the South West. These rivers form natural borders to Zambia, Zimbabwe and Botswana, while the region borders Angola in the North. The Zambezi Region lies at the heart of the KAZA TFCA, the world's second largest TFCA, with numerous national parks and wildlife migration corridors cutting through the region (Naidoo et al. 2018).

The Zambezi region has a population of 98.849 (2016) with over 70% of the residents living in rural areas (Namibia Statistics Agency 2017). In national comparison, the region has relatively suitable natural conditions for agriculture (Mendelsohn 2006). Although the majority of the rural population in Zambezi depends on crop production and cattle herding, there is very little intensification of agricultural activities or integration into formalized value chains (Hulke, Kairu, and Diez 2020). Katima Mulilo is the only urban center in the region and functions as an economic hub for cross-border trade and logistics, food procurement and processing, governmental control and other basic infrastructure, e.g. in health and education (Zeller 2009). 39 % of the population in the region live below the poverty headcount rate, compared to 27 % in the whole country (Republic Of Namibia 2016). Unemployment rates are also considerably high: almost 37 % of the working population and half of the population between 15 and 34 years of age is unemployed (Namibia Statistics Agency 2019).

3.1 Household survey and sampling

We use original HH data from a cross-sectional survey conducted between April and September 2019. Our dataset covers 652 HH in the rural part of Namibia's Zambezi Region. The questionnaire uses a 12-month recall period and covers key HH-level determinants of total and environmental income. A two-stage stratified random sampling approach was used with HH clustered in official enumeration areas (EA). First, EAs were stratified into c*onservation* (conservancies & national parks), *intensification* (agriculture & infrastructure) and *other* zones. Data on EAs was obtained from the Namibian Statistical Agency (NSA). Second, HH listings identified all HH in each EA, which were then randomly drawn from. Due to missing data that followed no specific pattern, 19 HH were excluded from the analysis.

3.2 Spatial covariate data

Our analysis considers established environmental income determinants (see section 2) and historical determinants of CBNRM establishment to control for selection bias. We pay considerable attention to spatially explicit contextual covariates by including Euclidean distances of HH to key infrastructure and environmental sourcing locations using Open Street Map (OSM) data. Determinants of supply and demand for environmental products are represented by SOC and nightlight radiation change as well as biomass change prior to the survey year. Nightlight radiation change data is derived from National Centers for

Environmental Information (NOAA) of National Aeronautics and Space Administration (NASA). SOC is provided by the International Soil Reference and Information Centre (ISRIC) which is publically available from the *African soil atlas* (Hengl et al. 2015). Both covariates are derived using a point value at the HH location. Biomass change is extracted from a biomass change map (see S5), which is generated using Wingate et al. (2016) methodology and ground truth data of Kindermann et al. (2021). The resulting summary statistics for all 633 HH are presented in Table 1 and data sources in S1.

4. Empirical strategy

We quantify environmental income using products that are *wild* and *uncultivated* and harvested from natural areas including forests (Angelsen et al. 2014). We calculate the use values of environmental products using local market prices. Indirect values, such as erosion control and flood prevention as well as non-use values such as cultural and existence values are not included. We quantify environmental income using the definition of Sjaastad et al. (2005) as follows:

> "[…] *natural rent realized, through consumption or alienation, within the first link of a market chain provides a precise and logically consistent measure of environmental income under conditions of perfect competition.*" (Sjaastad et al. 2005, 37)

Following this definition, we calculate gross environmental income of all products depicted in S2, with an average environmental gross income per HH member of 137.58 N$ and standard deviation (SD) of 656.60 N$. In order to measure environmental dependency, we calculate the share of environmental gross income on total gross income as percentage. This dependency is 13%, with a SD of 28%, indicating substantial spread and therefore varying importance of environmental income for HH.

4.1 Spatial determinants of collective action

Collective action outcomes are potentially biased by self-selection. Quasi-experimental empirical approaches, such as covariate matching can help to address selection issues, but remain subject to unobservable bias (Ferraro and Miranda, J. J. 2014). The statutory selection process to establish a conservancy in the study area is not regulated by universal and easily observable criteria that one could control for (Republic Of Namibia 1996, 4). This also holds for HH conservancy membership. We thus rely on propensity score weighted regressions and estimate the propensity score as follows:

$$T_i^C = \alpha + \beta X_i + \delta S_i + \varepsilon_i \qquad (1)$$

Where T_i^C indicates community conservancy membership of the HH i, X_i are socio-economic and demographic characteristics of HH i, S_i are pre-treatment, i.e. historical spatial covariates and ε_i indicate the idiosyncratic error terms, independent and identically distributed, with mean zero and constant variance.

We use covariates on (i) pre-treatment characteristics and (ii) data from pre-treatment spatial covariates of the HH to reduce unobservable bias. Choice of HH characteristics is guided by their potential role in affecting HH decisions to become conservancy members, while being exogenous, i.e. not influenced by CBNRM outcomes. For (i) we choose gender, age, education and ethnicity. For (ii) we choose pre-treatment nightlight, woodland cover, sand content, travel distance to regions capital, and distances to national parks, highway, schools and rivers. Descriptive statistics of these covariates are displayed in Table 1 and all treated (conservancy) and non-treated HH pre-weighting are described in S9. Member HH, the minority in the sample, are characterized by higher nightlight and lower distance to rivers. For the estimation we use covariate balancing propensity score (CBPS) following Imai and Ratkovic (2014). CBPS simultaneously optimize treatment assignment and covariate balance, increasing robustness against misspecification and potential biases (Imai and Ratkovic 2014). This is achieved via weighting the control group observations such that their weighted covariate distribution matches with that of the treatment group. This places greater emphasis on covariates with strong predictive power (see Imai and Ratkovic (2014) p. 245 – 247 for details).

4.2 Determinants of environmental income

To estimate environmental income and dependency, we proceed in two steps. First, we estimate double hurdle and a fractional logit model in a baseline regression to explore associations between predictors of environmental income and dependence, respectively. Second, we re-estimate these models including the CBPS as an additional weight to account for observed selection criteria.

Environmental income has the distinct characteristic to be zero for part of the population (see S3) leading to a zero-truncated dependent variable. Following Humphrey (2013), we consider these to be genuine zeros, i.e. HH making rational and utility maximizing decisions that are optimal with regards to allocation of time for generating income from the environment und known opportunity costs. This justifies using a hurdle model approach as zeros constitute a corner solution to the underlying constrained utility maximization problem. Generating income from the environment is also influenced by an *a priori* decision to engage in collection of environmental goods. These two decisions are therefore chronologically sequential, suggesting the use of a "full double hurdle model" (Jones 1992) or "double hurdle dependent model" (Garcia Villar and Labeaga 1996; Humphrey 2013). This model is estimated as follows:

$$Y_{1i}^* = \alpha_1 + \beta_1 X_{1i} + \delta_1 S_{1i} + \varepsilon_{i1} \qquad (2)$$

$$Y_{2i}^* = \alpha_2 + \beta_2 X_{2i} + \delta_2 S_{2i} + \varepsilon_{i2} \qquad (3)$$

$$Y_{2i} = Y_{2i}^* \qquad \text{if } Y_{1i}^* > 0$$

$$Y_{2i} = 0 \qquad \text{if } Y_{1i}^* \leq 0$$

where Y_{1i}^* is a latent variable capturing unobserved utility from deciding to collect environmental goods, Y_{2i}^* represents observed utility (i.e. income that is log transformed where

0 is kept at 0) from consumption and commercialization of environmental goods, generating income of HH i. X are all socio-economic and demographic characteristics of HH i, S are spatial characteristics of the HH i, and $\varepsilon_{i1}$and ε_{i2} indicate the idiosyncratic error terms, independent and identically distributed, with mean zero and constant variance. Table 1 displays all X and S variables. The model includes the inverse Mills ratio in the second (outcome) part of the estimation equation as it assumes $corr(\varepsilon_{i1}, \varepsilon_{i2}) \neq 0$ (Heckman 1979) and is estimated using *heckit* of the *sampleSelectioln* package in R (Toomet and Henningsen 2008).

For the case of environmental dependency, we estimate a fractional logit model using eq. 4, as percentage data is continuous but bounded between 0 and 1 (see S4) and use the same covariates as in eq. 2 and 3 (Papke and Wooldridge 1996).

$$Y_i = \alpha_1 + \beta X_i + \delta S_i + \varepsilon_i \qquad (4)$$

Informed by our estimations in 4.1, we use (i) sampling weights in the propensity score estimation stage (Eq.1) and (ii) sampling weights multiplied by CBPS weights in the outcome models (Eq. 2 to 4, except in the baseline specification) as suggested by Ridgeway et al. (2015). We present these findings in sections 5.3. Except in the baseline specification, we exclude trust and social network indicators from estimating eq. 2 to 4 and instead explore the effect of collective action on social network factors and trust as potential intermediate outcome indicators.

Our choice of covariates is based on their relevance as discussed in section 2 and both descriptive statistics and data sources are provided in section 3. To control for demand side determinants, we include HH characteristics such as HH head gender as male (dummy), age (in years) and education (in years), ethnicity (either Mafwe or Subia, as they are the main ethnicities), dependency ratio, and migration history. Asset endowment is represented by an asset index (using the first principal component from a principal component analysis (PCA)), except for agricultural land (in ha) and tropical livestock units (TLU), which enter as separate predictors that also indicate alternative livelihood options. We also control for shocks to the HH labor force, human-wildlife conflicts, and damage to crop, livestock and property.

HH exposure to and the engagement in collective action is represented by a conservancy membership dummy. We approximate social networks using information on with whom (quality) and how often (quantity) HH members have contact to (Zhang, Zhou, and Lei 2017). A trust index depicts the trust in different systems by the HH, using the first principal component from a PCA.

Market integration of the HH is represented via travel distance to the regions capital, Katima Mulilo (Schielein et al. 2020) as well as distances to the *trans-caprivi highway* (B8) and the C49 highway. Distance to the nearest river and to wildlife corridors serve as proxies for food income opportunities from wildlife and tourism potential. Nightlight radiation change from 2004 to 2013 approximates socio-economic development, measured in W m^{-2}. SOC in g/kg represents agro-ecological suitability. Finally, we use historical biomass change in order to avoid endogeneity problems, resulting from reverse causality of environmental income generation influencing current biomass. As a change indicates environmental regrowth as biomass regrows, we expect a positive correlation between biomass change and HH environmental income. We capture biomass change in tones between 2008 and 2018 surrounding the HH using a buffer of 1500m. This represents an average scale of interaction of the HH, which we derive using data of Mosimane et al. (2014), who identified interactions scales of HH with their environment for the KAZA TFCA.

4.3 Heterogeneous treatment effect analysis

As indicated in section 2, heterogeneous conservation outcomes from CBNRM were found in the region in prior work. Meyer et al. (2021) showed that conservation outcomes of collective action were moderated by tourism opportunities in the study area. To test whether this is reflected in livelihood choices and environmental income dependency in particular, we estimate eq. 2, 3 and 4 for two subsets. These subsets are defined by their distance to tourism areas, represented by tourism accommodation such as lodges and campsites using Open Street Map Data. We subset our dataset into areas below and above median distance to these tourism areas. We use the median due to its robustness against outliers. Additionally we test for a potential effect of conservancies on social networks and trust in these two subsets, which we report in S18.

All models are checked for multicollinearity, where we exclude variables with a variance inflation factor above five. Using a Breusch-Pagan test, we test for heteroscedasticity and address this issue through calculating heteroscedasticity-consistent coefficients, if applicable. The tobit model is estimated as heteroscedastic tobit regression model using *crch* (Messner, Mayr, and Zeileis 2016).

5. Results

5.1 Baseline results

We start by exploring the baseline results of estimating equations 2, 3 and 4 without CBPS-weighting in columns 2, 3 and 4 of Table 2, respectively. Selection and quantity models are estimated jointly using a double hurdle model and environmental dependency is estimated using a fractional logit model.

Results from column 2 and 3 can be interpreted as semi-elasticities, i.e. a *relative* change in selection probability and quantity of environmental income from an *absolute* change of one unit in the explanatory variables (Verbeek 2012). Results from column 4 show a percentage change in dependency given an absolute change of one unit in the explanatory variables. Collective action, represented by conservancy membership, expectedly favors the engagement in environmental product collection by 21% and increases the amount derived by 52%. Membership also substantially increases environmental dependency by 17%, indicating strong and relevant effects of membership on all outcomes. Trust increases the probability of HH to collect products from the environment by 9% and quantity collected by 16%. Effect sizes of social networks on all outcomes are small. An increase in nightlights at the HH location of one W m^{-2} is associated with a decrease of 6% in environmental product collection quantity, reflecting socio-economic development away from reliance on the environment. SOC exhibits a small but negative association with environmental income and dependency, reflecting agricultural income opportunities. Biomass change has a small positive effect on environmental income but no effect on dependency. Various other confounding variables are correlated with environmental income and dependency (see S10).

5.2 Spatial determinants of collective action

Results from estimating eq. 1 are depicted in table 3 and identify HH-level and spatial determinants of collective action.

In the CBPS regression (column 2), pre-treatment woodland cover before conservancy establishment is the single most important determinant of conservancy membership. Additionally, ethnicity of the HH head as well as pre-treatment nightlight and travel distance are relevant factors. As CBPS optimize the covariate balance, treatment assignment is modelled optimally. This is in line with estimates of the GLM probit model (column 3). As CBPS generates a high covariate balance, expressed through low difference in means as seen in S8, we use these in 5.3, estimating the causal effect of conservancy membership on HH environmental income and dependency.

5.3 Influences of collective action and spatial determinants on environmental income and dependency

Using CBPS for estimating spatial determinants of collective action substantially improves covariate balance and overlap of the propensity score (see S7). We use this score to calculate weights that weigh each observation according to their probability of being a conservancy member (see S15) and then re-estimate equation 2 to 4. Results are shown in table 4 and indicate the effect of collective action on the choice of selecting environmental income as livelihood source (column 2) environmental income quantity (column 3) and environmental dependency (column 4) using CBPS propensity score weights.

The findings regarding conservancy membership are not qualitatively different from our baseline regression. However, the average treatment effect of membership on engagement in environmental product collection increases by 5% to 25%. Quantity and dependency are also affected positively with large effect sizes. Hence, among conservancy members more HH extract on average higher values of environmental products compared to non-conservancy members. Effect sizes of spatial determinants vary, but remain qualitatively in line with baseline results. Positive biomass change is associated with higher environmental income quantity when comparing conservancy members to similar non-members. Estimates using GLM probit model weights in the robustness checks suggest that findings are stable (see S13). Additionally, immigrants and Subia ethnicities are more likely to collect environmental products, whereas Mafwe ethnic groups do harvest more environmental products. Shocks generally decrease collection and dependency, as timber product collection is labor intensive (See S12).

5.4 Heterogeneous treatment effects

As hypothesized in section 2, we suspect that treatment effects are heterogeneous and moderated by tourism opportunities, which incentivize HH to preserve natural habitat and associated ecosystem quality. As a proxy, we use below and above median distance to tourist accommodation, such as lodges and campsites to subset our sample.

In relative proximity to tourism accommodation, association of HH conservancy membership with environmental income and dependency are positive and effect sizes are large. HH are 57% more likely to engage in environmental product collection and generate 142% more income from the environment. They are also 61% more dependent on the environment. On the contrary, conservancy members tend to be less dependent than non-conservancy members on the environment outside tourism areas by 81%. Conservancy members compared to non-conservancy members are also 21% less likely to engage in environmental product collection. Hence, conservancy membership seems to be fostering human-environment interactions, but only when HH are in relative proximity to tourism, which requires relatively undisturbed landscapes (Meyer et al. 2021). As expected (see section 2), social capital indicators do not seem to be affected by this contextual moderation effect (S18) and unweighted results are qualitatively similar (S14).

In relative distance to tourism accommodation, higher SOC and corresponding agricultural suitability is associated with lower levels of environmental income and dependence of HH. HH have 39% higher agricultural income in relative distance to tourism accommodation, which supports this finding. Nightlight radiation and biomass change appear to be less relevant and robust predictors of environmental income and dependency once contextual variation in tourism opportunities is accounted for.

5.5 Robustness Checks

To gain further confidence in our results, we conduct three additional robustness checks. We estimate alternative specifications that include (1) the estimation of a standard Tobit model, (2) control for different matching setups and (3) test for spatial autocorrelation of the depended variable using three different spatial weights matrices representing three different neighborhood relations.

First, we estimate a standard Tobit model for determinants of environmental income to gain insights to what extent results have been driven by using a hurdle model. Results are reported in S6 and confirm the results presented in Section 5.1.

Second, to assess whether the results from the post-matching regression are driven by matching specifications we compare the estimated ATT by CBPS weights with a propensity score estimates using inverse probability weighting (ipw), implemented in the R package *ipw* by van der Wal and Geskus (2011) and nonparametric nearest neighbor matching, implemented in the R package *MatchIt* by Ho et al. (2011). ATT estimates of the effect of conservancy membership on environmental income selection, quantity and dependency consistently range from 0.13 to 0.26, 0.44 to 0.58 and 0.16 to 0.32 respectively (see S16), suggesting robustness of our reported ATT results.

Third, as potential autocorrelation of the dependent variable may influence estimation results, we tests for it using Lagrange Multiplier diagnostics for spatial dependence following Anselin (1988), implemented using *lm.Lmtests* of the R package *spdep*. In order to identify relevant interaction scales of HH, we follow Avelino, Baylis, and Honey-Rosés (2016) and select scales that matches the decision-making unit, i.e. the unit that reflect how HH interact with their neighbors. For this, we use three different weights matrices to indicate HH neighborhood: short (0m – 500m), medium (501m – 1500m) and far (1501m – 3000m). These represent different scales of spatial interaction of the HH with their environment for the KAZA TFCA by Mosimane et al. (2014), which we interpret also as relevant neighborhoods. All robust LM tests (SAR, SEM and SARAR) do not reject the null hypothesis of significant spatial autocorrelation in the dependent variable. Thus, following Gibbons and Overman (2012), no qualitatively different results can be expected when using spatial regression approaches.

6. Discussion and Conclusion

CBNRM schemes seek to promote sustainable income generation from natural resources by solving commons problems. Yet, there is little knowledge on the role of these schemes in affecting how rural households interact with their environment under varying economic contexts. We examine how community conservancies in Namibia's Zambezi Region affect environmental income and dependency with and without exposure to tourism-related income opportunities.

In our sample, gross income from the environment accounts for about 13% of total gross income on average, with poorer HH being more dependent. This is in line with findings of Cavendish (2000), Kamanga, Vedeld, and Sjaastad (2009) and Angelsen et al. (2014). HH generally follow a multi-livelihood strategy with an average of 2.67 different income sources similar to findings by Nielsen, Ø. J. et al. (2013).

We find that HH, which are members in conservancies, are 25% more likely to collect environmental products and generate on average 55% more environmental income than households that are not members in such formalized CBNRM schemes. Conservancy membership is a less reliable predictor of environmental dependency, but the effect size (32%) is relevant. In earlier work, also based on detailed environmental income accounting, Angelsen et al. (2014) and Ojeda Luna et al. (2020) fail to detect any statistically significant effect of collective forest management on forest income. Our result differs in that we do find a higher probability to select and generate quantity of environmental income. This difference may be explained by our empirical strategy and our regional focus. First, Angelsen et al. (2014) does not adopt a counterfactual-based regression approach and second, the global study excludes Namibia. Ojeda Luna et al. (2020) look at rainforest users in Ecuador, a very different bio-geographical context.

Importantly, prior work largely focusses on average impacts of collective natural resource management, which could by masked by contextual moderation effects. Here we find that CBNRM has different effects on environmental income depending on whether HH are exposed to tourism activities. This is in line with Meyer et al. (2021) who found Namibian conservancies to work in favor of the region’s woodland resources only when wildlife presence serves as a potential attractor for national and international tourism. Our result here corroborates this finding by showing that HH in these areas are also more often engage in livelihood strategies that rely on the environment. A similar observation is reported by Ojeda Luna et al. (2020) for a rainforest environment in Ecuador, where tourism is not primarily wildlife-oriented. In our study region, however, conservation has historically had an almost exclusive focus on wildlife. In combination with Meyer et al. (2021), our finding suggests that wildlife tourism can have positive externalities on vegetation biomass (and thus carbon sequestration) and that this effect is driven by synergies in local people's livelihood choices, rather than just being a result of tourism enterprises selecting into particular landscapes. This potential causal pathway warrants future research.

If HH in areas that provide wildlife tourism opportunities engage more in environmental income generation, do they cut back on other income sources? Community conservation involves establishment of management zones, which (at least *de jure*) exclude certain land uses, especially agriculture (Mbaiwa 2011). We find mean income from agriculture in relative proximity to tourism accommodation to be 37% lower than outside these areas and 23% lower than average income from agriculture. While this suggests that conservancy members implement the CBNRM restrictions more rigorously, this is not necessarily a result of differentials in social capital or trust (see results in S17). Instead, real or expected economic opportunities by conservancies also seem to provide sufficient private incentives to align livelihood choices with conservation objectives.

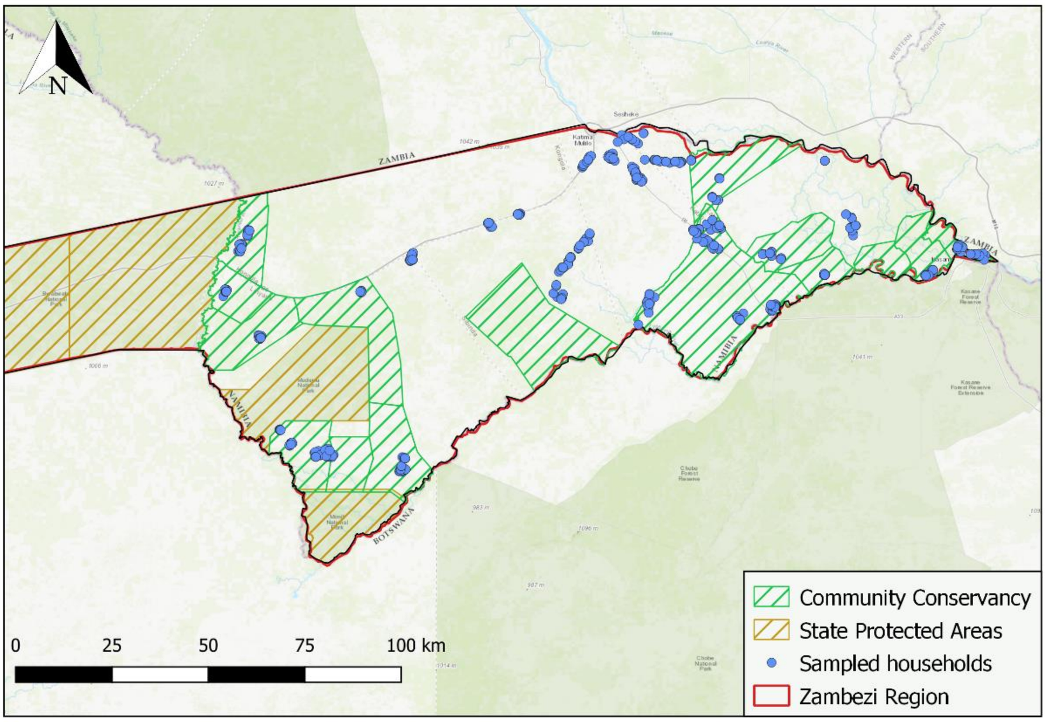
Watmough et al. (2019) and Yeh et al. (2020) show that spatially explicit covariates derived from remote sensing products can help to predict poverty in rural areas more accurately. From our three spatially explicit predictors, SOC predicts environmental income (or the lack thereof) in non-tourism areas where agriculture is the dominant livelihood strategy. This is in line with findings of Yamano and Kijima (2010), who show that soil organic matter, using on-the-ground soil sampling, is positively associated with household income. We argue that also remotely sensed soil quality measures are adequate predictors of rural income and poverty. Our findings were less encouraging in terms of finding direct associations between nightlight data and biomass measures and environmental income, probably because average changes in these predictors over time were not sufficiently large to affect outcomes.

Like Pritchard et al. (2019), who focus on neighboring Zambia, we find no robust relationships between woodland resource availability and environmental income, while assuring that we compare CBNRM members with non-members exposed to similar woodland resource levels prior to CBNRM establishment. Pritchard et al. argue that HH can generate woodland resources even on ecologically degraded lands and draw upon kin and social networks, which facilitate access to resources beyond village borders. Both these strategies would seem to be associated with additional costs vis-à-vis households with better access to woodland resources and thus be reflected in livelihood choices. Our results in Table 2 and S17 suggest that social networks are somewhat positively correlated with environmental income, but not causally related to CBNRM membership. Hence, the relationship between natural resource endowment (including access) and rural household income requires further research including on the historical determinants of natural resource access and endowment.

Our study has implications for the general debate on human-environment interactions and environment-development tradeoffs (Barbier 2010). For large conservation areas to be sustainable, including transboundary areas such as KAZA, implementers must provide spatially targeted incentives, especially in sub-regions where synergies between conservation and development turn in to tradeoffs. At global scale, nature protection may increase rural welfare on average (Naidoo et al. 2019), but context-driven impact heterogeneity can still result in local livelihood strategies being incompatible with conservation.

Tables and Figures

Figure 2: Zambezi Region, Namibia



Source: own illustration

Table 1: Outcome and covariate data summary statistics

Group		Variables	mean	sd	median	min	max
Income	1	Environmental gross income per head	137.58	656.60	0.00	0.00	13750
	2	Environmental income share	0.13	0.28	0.00	0.00	1.00
Household characteristics	3	HH head male	0.52	0.50	1.00	0.00	1.00
	4	HH head age	51.55	17.59	49.00	20.00	91.00
	5	HH head education [years]	5.41	3.15	6.00	0.00	15.00
	6	HH head inmigration	0.71	0.45	1.00	0.00	1.00
	7	Mafwe Ethnicity [dummy]	0.22	0.42	0.00	0.00	1.00
	8	Subia Ethnicity [dummy]	0.39	0.49	0.00	0.00	1.00
	9	Dependency ratio	40.79	23.75	42.86	0.00	100.00
	10	Asset index	3.00	1.42	3.00	1.00	5.00
	11	Agricultural land [ha]	9.56	18.77	4.94	0.00	300.00
	12	TLU	5.05	11.98	0.34	0.00	122.80
	13	Labor shock [dummy]	0.60	0.71	0.00	0.00	3.00
	14	Wildlife conflict crop damage [dummy]	0.14	0.34	0.00	0.00	1.00
	15	Wildlife conflict livestock damage [dummy]	0.08	0.27	0.00	0.00	1.00
	16	Wildlife conflict property damage [dummy]	0.02	0.14	0.00	0.00	1.00
Collective action	17	Conservancy member [dummy]	0.38	0.49	0.00	0.00	1.00
	18	Social Network index	25.67	24.57	19.48	0.00	100.00
	19	Trust index	2.99	1.42	3.00	1.00	5.00
Market Integration	20	Travel distance [h]	0.25	0.15	0.25	0.02	0.71
	21	Distance to B8 & C49 [km]	8.46	13.90	2.77	0.00	59.04
	22	Distance to rivers [km]	38.99	39.00	20.40	1.00	151.48
	23	Distance to wildlife corridor [km]	10.64	12.79	4.72	0.00	37.93
Spatial	24	Nightlight radiation change [W m^{-2}]	0.82	1.96	0.00	0.00	14.00
	25	SOC [g/kg]	9.92	3.36	9.00	4.00	23.00
	26	Sand content [g/kg]	721.60	68.66	731.00	387.00	833.00
	27	Biomass change 2008 – 2018 [t/ha]	-2.67	8.40	-3.47	-46.40	47.74

Source: own illustration

Table 2: Effects of collective action and spatial determinants of environmental income and dependency

	Income		**Dependency**
	Selection	Quantity	
Intercept	-0.060 (0.404)	-0.128 (1.374)	0.119 (1.183)
Collective action & social capital			
Conservancy member	**0.207** (0.122)$^{\cdot}$	**0.518** (0.217)*	0.166 (0.247)
Social Networks	**0.006** (0.002)**	0.008 (0.006)	-0.003 (0.004)
Trust	**0.091** (0.037)*	**0.162** (0.092)$^{\cdot}$	0.028 (0.070)
Spatial determinants			
SOC	-0.004 (0.018)	-0.008 (0.015)	-0.031 (0.038)
Nightlight change	0.012 (0.031)	**-0.063** (0.029)*	-0.010 (0.079)
Biomass change | 1500m Buffer	0.004 (0.007)	0.010 (0.007)	-0.000 (0.012)
Other Controls			
HH Characteristics		Yes	
Shock & wildlife conflict		Yes	
Distances		Yes	
invMillsRatio	**2.664** (1.539)$^{\cdot}$		
logLik	-405.299		-195.619
Num. obs.	633	309	633
R^2		0.848	
Adj. R^2		0.834	
RMSE		0.768	

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$

Robust SE clustered at village level for fractional logit are provided

Note: Estimations based on unweighted data set

Source: own illustration

Table 3: Household and spatial determinants of HH conservancy membership

	Covariate Balancing Propensity Score	Probit GLM
Intercept	**-1.61** (0.42)***	-1.06 (0.87)
Male	0.07 (0.13)	0.03 (0.11)
Age	0.01 (0.15)	0.00 (0.00)
Education [years]	-0.01 (0.15)	-0.01 (0.02)
Mafwe	-0.20 (0.15)	-0.18 (0.15)
Subia	-0.12 (0.15)	-0.07 (0.13)
Nightlight 1998	0.15 (0.15)	**0.10** (0.05)*
Woodland cover 1994	**0.89** (0.14)***	**0.52** (0.21)*
Sand content	0.00 (0.07)	0.00 (0.00)
Travel distance	-0.16 (0.18)	-0.12 (0.57)
Distance to National Park	-0.03 (0.21)	**-0.02** (0.00)***
Distance to highway	0.01 (0.18)	0.01 (0.01)
Distance to school	-0.01 (0.20)	**-0.00** (0.00)**
Distance to river	-0.01 (0.29)	**-0.00** (0.00)$^{\cdot}$
AIC	726.88	755.88
BIC	738.12	818.21
Log Likelihood	-349.44	-363.94
Deviance	698.8827	697.98
J-statistic	0.0004	
Num. obs.	634	

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$

Source: own illustration

Table 4: Effects of collective action and spatial determinants of environmental income and dependency (CBPS weighted sample)

	Income		Dependency
	Selection	Quantity	
Intercept	**0.772** (0.299)**	**1.222** (0.557)*	0.569 (0.741)
Collective action			
Conservancy member	**0.252** (0.090)**	**0.554** (0.220)*	0.321 (0.213)
Spatial determinants			
SOC	-0.010 (0.014)	-0.014 (0.016)	-0.024 (0.032)
Nightlight change	0.023 (0.027)	-0.026 (0.032)	-0.011 (0.064)
Biomass change | 1500m Buffer	0.009 (0.006)	**0.016** (0.010)$^{\cdot}$	0.004 (0.014)
Other Controls			
HH Characteristics		Yes	
Shock & wildlife conflict		Yes	
Distances		Yes	
invMillsRatio		**2.553** (1.335)$^{\cdot}$	
logLik	-622.968		-199.783
Num. obs.	633	309	633
R^2		0.870	
Adj. R^2		0.859	
RMSE		0.926	

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$
Robust SE clustered at village level for fractional logit are provided

Source: own illustration

Table 5: Effects of collective action and spatial determinants of environmental income and dependency in tourism and non-tourism areas (CBPS weighted sample)

	Selection	**Quantity**	**Dependency**	**Selection**	**Quantity**	**Dependency**
	Tourism Area			*Non-Tourism Area*		
Intercept	-0.150 (0.456)	-1.714 (1.502)	-0.794 (1.986)	**3.971** (0.564)***	**5.656** (1.139)***	**5.876** (1.766)***
Collective action & social capital						
Conservancy member	**0.546** (0.137)***	**1.424** (0.549)*	**0.606** (0.342)$^{\cdot}$	-0.213 (0.141)	-0.217 (0.179)	**-0.808** (0.409)*
Spatial determinants						
Nightlight change	0.048 (0.038)	0.070 (0.054)	0.003 (0.117)	0.035 (0.049)	-0.058 (0.047)	-0.059 (0.114)
SOC	0.021 (0.020)	**0.083** (0.026)**	0.032 (0.058)	**-0.133** (0.028)***	**-0.159** (0.061)*	**-0.352** (0.112)**
Biomass change | 1500m Buffer	0.003 (0.010)	0.004 (0.010)	-0.006 (0.019)	-0.003 (0.010)	-0.005 (0.009)	0.000 (0.026)
Other Controls						
HH Characteristics			Yes			
Shock & wildlife conflict			Yes			
Distances			Yes			
invMillsRatio		**3.988** (1.618)*			**1.422** (0.842)$^{\cdot}$	
logLik	-287.888		-111.517	-268.060		-88.898
Num. obs.	317	165	317	316	144	316
R^2		0.887			0.901	
Adj. R^2		0.868			0.881	
RMSE		0.822			0.983	

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$
Robust SE clustered at village level for fractional logit are provided
Source: own illustration

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