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Research article

Marine fishery dependence, poverty and inequality nexus along the coastal lowlands of Kenya

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Abstract: This paper examines the nexus between marine fishery dependence, poverty and inequality among households in coastal lowlands of Kenya, specifically, Kilifi County. Data for the study were collected from 384 randomly selected households through structured pretested questionnaires. The study used the multidimensional poverty methodology and multivalued treatment effect model to determine the marine fishery dependence of households, poverty, and inequality nexus. Findings from the study show that increasing ocean fishery dependence is associated with increased poverty and inequality among the dependent households. However, it is worth mentioning that other factors may as well affect poverty. Results also revealed that fishing was not a choice, but rather a necessity with approximately 71.3% of the dependent households reporting a lack of alternative livelihood options. More so, the dependent households that pursued diversification livelihood strategies had a lower deprivation score at 0.29 compared to 0.47 that engaged solely in fishing. Welfare policies such as the establishment of Beach Management Units (BMU), No Take Zones (NTZs), locally managed marine areas (LMMAs), and information networks have been put in place to promote the livelihoods of the fishing communities. However, their implementation has been ineffective leading to social exclusion and hence poverty traps among the poorest dependent households. The study, therefore, recommends strengthening existing governance options while putting a special focus on gear regulations.

Keywords: marine fishery dependence; multidimensional poverty; inequality; multivalued treatment effect model; heterogeneous treatment effect; dose response function; Kenya

JEL Codes: Q5, Q50, Q56.

1. Introduction

Natural resource contributions to rural livelihoods have been documented across a wide range of literature (Angelsen et al., 2014; Soltani et al., 2014). They serve as an indispensable source of income and subsistence for most households, especially in rural parts of developing countries. Marine resources are valuable in providing food security, livelihood, and mitigation of climate change as well as enhanced economic growth through trade (Wamukota, 2009; Akongyuure et al., 2017). The marine landing in Kenya is approximately 9000 tonnes per year (Van Hoof and Stein, 2017). It has an annual economic value, which estimates at over US$4.4 billion (Muigua, 2018), and remains one of the dominant economic activities along the coastal region in Kenya (Degen et al., 2010; Cinner et al., 2011; CGOK, 2013).

The paradox of poverty in resource dependence has well been acknowledged, especially in the fishery (Cinner et al., 2011; Stanford et al., 2013; Samoilys et al., 2017). Economic theory argues that there is a lack of cooperation in the management and sustenance of common-pool resources due to the conflicting nature of the dependent households' individual and collective interests (Velez et al., 2009; Ostrom and Hess, 2010). Pure self-interest is grounded within the assumption of a higher rate of time preference, which accelerates fishing activities and reduces investments for sustainable marine resource management (Stanford et al., 2013). In contexts of low capacity to regulate the commons coupled with increased fishing activities and mechanization, over-exploitation becomes unavoidable, leading to the tragedy of commons.

Literature indicates that the positive relationship between fishery and poverty is attributed to higher dependency on one economic activity that spurs vulnerability due to socio-institutional constraints (Cinner et al., 2011; Hicks et al., 2017). Further, the marine resource is under the threat of environment and climate change, such as rising sea levels, ocean acidification, and higher sea surface temperature. It is likely that higher dependence on this type of livelihood option limits the dependent households' capacity to enhance their material wellbeing due to unsustainable stream of income caused by the wide range of shocks (Edirisinghe, 2015). These conditions create a downward spiral of overexploitation, which leads to poverty, and poverty results in overexploitation, a phenomenon known as a poverty trap, which is common in small scale fishery (Cinner et al., 2012; Stanford et al., 2013).

The objective of this paper is to determine the association between ocean fishery dependence and poverty and inequality among households in Kilifi County, Kenya. In this sense, it contributes to the existing literature in several ways. Firstly, it contributes to the literature on natural resource dependence and welfare implications. To the best of our knowledge, the study seems to be the first to apply the multivalued treatment effect model. Secondly, the study provides insights into the heterogeneity of effects by classifying dependency. For social policy and program planners, unraveling heterogeneity in effect is important as it will give them insights into developing targeted interventions. Thirdly, the study provides empirical evidence built on a case study in Kenya's coastal lowlands, a region affected by historical land injustices. More so, ocean fishery is a critical resource with welfare implications. Therefore, the information obtained from this study could be useful in designing policies and strategies for enhancing sustainable livelihood portfolios.

The remainder of the article is structured as follows; the second section presents the conceptual framework; section three presents material and methods for the study; section four presents the discussion of the econometric results, and section five presents the conclusions and policy implications of the study.

2. Conceptualizing marine fishery dependence, poverty and inequality

We operationalized the ocean fishery dependence, poverty, and inequality using Sen's functioning and capability framework. The framework is concerned with the person's freedom to choose his/her functionings, which requires a minimum level of well-being brought about by a set of attributes (Sen, 1993). In Sen's verdict, poverty in the fishery is attributed to deprivation of capabilities and entitlements that limit fishers' freedom to enhance their lot. This implies that poverty in fishery-dependent households is not exclusively dependent on market opportunities, catch abundance, or the nature of the resource. It is also influenced by how benefits derived from the resource are used and whether basic services are provided (Jentoft et al., 2010). Poverty is a multidimensional concept; therefore, to promote fishers' welfare, their freedom needs to be enhanced in a broader concept than merely promoting freedom in common-pool resources (Hickey and Du Toit, 2013).

The process of choosing a functioning vector from the capability set is inescapably socially-embedded even though it is an individual that makes a choice (Sen, 1993). However, social arrangements have been reported to suppress freedoms among the poor reproducing relations of inequality and marginalization (Hickey and Du Toit, 2013). Given that small-scale fishery is often equated to poverty, exclusion of dependent households due to social identity is inevitable, leading to inequality in the sector. Further, with respect to the link between ocean fishery dependence, poverty, and inequality, many studies have been conducted in different areas and at different scales, making generalizations difficult. However, a dominant narrative in natural resource literature is that fishery dependence is associated with higher poverty and inequality (Degen, 2010; Stanford et al., 2013; Eggert et al., 2015). The reason for this is that the dependent households are constrained by socio-cultural, institutional, and economic factors (Stanford et al., 2013). This results in capability deprivation, which suppresses fishers' freedom to pursue their entitlements in education, health, sanitation, and living standards. Therefore, understanding the linkage between ocean fishery dependence, poverty, and inequality among households in Coastal Lowlands of Kenya is critical for developing appropriate policy options and improving the welfare of the dependent households.

3. Materials and methods

3.1. Description of the study area

The study was carried out in Kilifi County (Figure 1), located in the coastal region in Kenya. It borders the Indian Ocean to the east, and Mombasa County to the South, covering an area of 12370.8 km^2 (CGOK, 2018). Fishing and tourism are the major economic activities in the region due to the wide coverage of white sandy shores along the Indian Ocean. Yet, fish catches have been reported to decline due to the intrusion of salt mining companies, use of destructive gears, and climate change (CGOK, 2013). More so, the Ocean fishery dependence has been long linked to the Bajun ethnic group that is being regarded as the fishers' par excellence. However, since the

1960s, Mijikenda has engaged in this economic activity resulting in an increase in the number of dependent households (Degen et al., 2010). This is due to a significant level of poverty-related to historical injustices of land and intertwined socioeconomic constraints. In particular, marine fishery in Kilifi County is small scale, depends strongly on seasons, and is characterised by multiple use of gears and targeting a wide range of species (Samoilys et al., 2017). Further, through landing sites, fisheries management is organized into Beach Management Units to provide local control of fisheries (Paula et al., 2015; Wanyonyi et al., 2016).

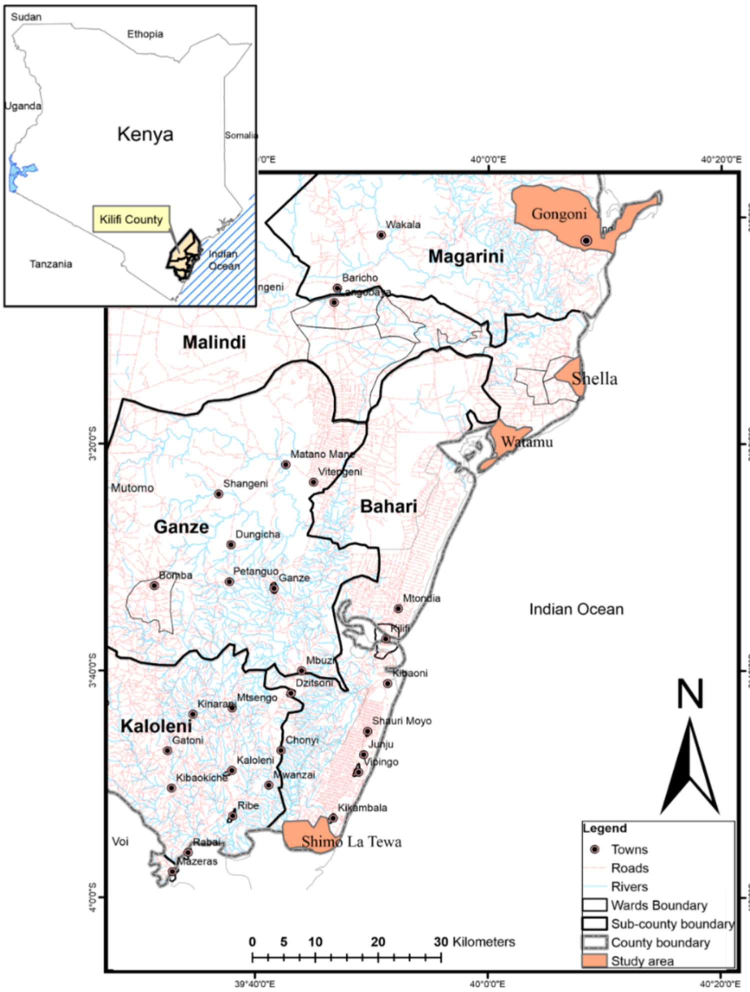

Figure 1. Map of the Kilifi county (Source: Geography Department, Egerton University-Kenya).

3.2. Research design, sampling and data management

The study used exploratory research design to explore marine fishery dependency, poverty, and inequality among households in Kilifi County. The research design was selected because it is flexible and hence more appropriate in a study area where the subject matter is yet to be exploited. Further, a multistage sampling technique was applied to select respondents for the study. In stage one; Kilifi County was purposively selected due to the existence of ocean fishery resource in the region and the higher level of poverty (71.7%) and inequality (0.565) (Ngugi et al., 2013). In stage two, the purposive sampling method was used to select 4 wards [1] (Shella, Watamu, Gongoni, and Shimolatewa) from a population of 35, because they are located along the Indian Ocean and therefore, offer important ground for artisanal fishing. Finally, in the last stage, simple random sampling was applied in the selection of 384 households spread over the 4 wards in Kilifi County. The sampling design was preferred because it reduces sampling bias by ensuring that all households have the same chance of being selected into the sample. Determination of the household sample size was arrived at using Equation (1) (Cochran, 1977).

$$n_0 = \frac{z^2 \times p(1-p)}{e^2} \tag{1}$$

where: n_0 presents minimum estimated sample size, z is the value of the t-distribution corresponding to the selected value of alpha 0.5 = 1.96, p is the population proportion estimate, and e is the margin of error. When p is unknown, it is usually put at 0.5 and e at 0.05 (Cochran, 1977).

Data was collected using a pretested semi-structured questionnaire (designed by the authors) through face-face interviews with the household heads by well-trained enumerators. We offered proper training to all enumerators to ensure consistency and plausibility of the data. Also, the structured questionnaire was carefully tested to determine the validity of the questionnaire and the convenience of the data collection process (validity score = 0.823; reliability score = 0.91). More so, the study relied on the conducted pilot study and thorough probing to assure quality control in data. This was after seeking informed consent from the respondents. Prior to data collection, permission from the National Commission for Science, Technology, and Innovation (NACOSTI) was obtained.

The household questionnaire comprised of different sections on household livelihoods options (Marine fishery and related activities, agriculture. Wage employment, self-employment, and remittances). Marine fishery and related activities included fishing, fish trading and processing, boatbuilding, and selling of fish equipment. Data on the catches, revenues, and cost of fishing were recorded. Also, a household dietary diversity score was introduced to capture food that the households consumed in the last twenty-four hours. Questions on dimensions and indicators of multidimensional poverty index were established to determine households' poverty status. Additionally, the household questionnaire contained a shocks section to record all shocks experienced by the households in the last three years. Data were analyzed using SPSS and STATA computer software.

3.3. Measurement of marine fishery dependence and household income

Household's marine fishery dependence level was measured by dividing the household income from the ocean fishery resource with the total household income. Thus, the dependent variable was expressed as the proportion of the total household income, as described in Equation (2). This was critical to capture ocean fishery as a continuous variable with the assumption that higher income from the livelihood option indicates increased marine fishery dependence.

$$Y^* = \frac{\text{Household Income from Ocean Fishery Resource}}{\text{Total Household Income}} \tag{2}$$

[1]In Kenya, a ward is an administrative unit that is smaller than a sub-county but larger than a village.

where: Y^* is the ocean fishery dependence ranging between 0 and 1. The numerator represents household income generated from ocean fishery and related activities (fishing, fish trading and processing, boatbuilding, and selling of fish equipment) less associated expenses. At the same time, the denominator reflects total household income. Total household income involved a summation of income from crops (value of crop produce less cost of inputs), net fisheries-related income and livestock income (sum of income obtained from selling of live animals less cost incurred in purchasing live animals and inputs), household members' wages and salary, remittances and business income (Mathenge et al., 2010).

3.4. Measuring poverty

Previous literature has been built on the Forster-Greer-Thorbecke (FGT)[2] poverty index to estimate income poverty[3] (Akongyuure et al., 2017). However, the income poverty has several drawbacks that include; using income as the lone indicator of measuring the wellbeing of an individual and hence limited since it does not reflect and incorporate the key dimensions of poverty associated with the quality of life. Also, the income poverty approach does not guarantee that households with income at or above the poverty line would use their incomes to purchase the minimum basic needs. This implies that households may be non-poor in terms of income but deprived of basic needs (Kabubo-Mariara et al., 2011). This infers that income poverty is an indirect approach to assess the ability of the household to satisfy basic needs. Therefore, the study focused its analysis on the multidimensional measurement of poverty.

Multidimensional poverty[4] offers an added advantage compared to income poverty since it enables the researcher to assess directly the types of basic needs a household can actually satisfy. Also, the approach allows for decomposability and offers freedom in assigning different weights to different indicators (Kabubo-Mariara et al., 2011). In this sense, multidimensional poverty indicators for quantitative impact analysis and weighted procedures for the multidimensional poverty index (MPI) were applied. The approach was preferred to factor and cluster analyses because it provides absolute poverty levels and allows for poverty comparison across different settings (Ogutu and Qaim, 2018).

The study used the approach applied by Alkire and Foster (2011) and Ayuya et al. (2015), who recommended various dimensions of poverty, including living standards, health, education, and assets, and several indicators for deprivation assessment as indicated in Table 1. The dimensions were derived from human development components such as Millennium Development goals (Ayuya et al., 2015). Further, indicators were weighted equally using nested weight structure (Alkire and Foster, 2011). In this sense, for a house to be defined as multidimensional poor, poverty cut off of 1/3 on the total weighted indicators was used (Ayuya et al., 2015).

[2]Forster-Greer-Thorbecke (FGT) poverty index is a poverty measure in a population defined as; $y_i = \frac{z - v_i}{z}$, where, v_i = Per capita income of household i, z = Poverty line; thus, households with income above the poverty line are assigned zero and Y_i = Income poverty gap that is a continuous variable ranging between zero and one.

[3]Income poverty refers to a failure to satisfy basic needs using per capita income as a threshold.

[4]Multidimensional poverty refers to deprivation in human life dimensions such as health, living standard, education and assets.

Table 1. Dimensions and indicators of the multidimensional poverty index.

Dimension and indicator	Description and deprivation cutoff
Education	
School achievement	Deprived if the household head and spouses have not completed the primary level of education
School attendance	Deprived if the household has school-aged children not going to school
Standard of living	
Electricity	Deprived if the household has no electricity
Drinking water	Deprived if the household does not have access to safe drinking water or they have to walk over 30 min to get safe drinking water
Sanitation	Deprived if the household has no descent pit latrine
Flooring	Deprived if the household house is earth
Assets	
Phone	Deprived if the household does not own a mobile phone
Radio and/or television	Deprived if the household does not own at least radio
Vehicle	Deprived if the household does not own at least a bicycle
Health	
Nutrition 1	Deprived if the household reports a household dietary diversity score of 6 and below out of the possible 12 food groups
Nutrition 2	Deprived if the household relies on relief food or any case of malnutrition in the past 2 years
Access	Deprived if the household has difficulty in meeting basic public hospital bills

Source: Adapted from Ayuya et al. (2015).

The MPI measures for each household were calculated first by determining the total household deprivation score through the summation of all weighted values, as shown in Table 1. The score was ranging between zero and one, with a higher value indicating higher deprivation level. Second, it involved the determination of the multidimensional poverty dummy (headcount ratio), which is assigned one if the total deprivation score of the household is greater than or equal to a common threshold of 0.33, and zero otherwise. Third, it involved the determination of multidimensional poverty intensity, which equals the summation of deprivation scores of the poor divided by the number of poor people (Alkire and Santos, 2013). It is noteworthy that MPI has several drawbacks such as the indicators may reflect the output instead of capabilities. Also, the approach tends to overlook the group's dimensions such as nutrition. However, it remains the best available approach to measure poverty (Alkire and Santos, 2013).

3.5. Measuring inequality

Inequality[5] was measured using separate inequality measure through a positive multiple of variance (Equation 3). The method was preferred to integrated inequality approaches because it provides intuitive interpretations of the FGT family of poverty measures, including incidence, intensity, and adjusted headcount ratio. In our context, a separate inequality measure offered a vital

[5]Inequality implied a difference in material deprivations between different households.

framework in studying disparity in materials deprivation across the dependence levels. In this sense, inequality among the households was captured across deprivation scores obtained through the accounting approach (Alkire and Seth, 2014) as described;

$$l(x) = \frac{4}{t}\sum_{i=1}^{n}[x_i - \mu(x)]^2 \tag{3}$$

where $l(x)$ represents inequality among the households, t is the sample size, x_i is the individual's deprivation scores, and $\mu(x)$ is the average deprivation score for the sampled households. The formula was applied instead of $\Sigma^t_{i=1}[x_i-\mu(x)]^2/t-1$[6] since it satisfies population replication invariance[7], which states that $l(x') = l(x)$ (Alkire and Seth, 2014). Prior to running the model, endogeneity test was performed on ocean fishery dependence on poverty and inequality using Durbin–Wu–Hausman test (Cameron and Trivedi, 2005).

3.6. Specification of multivalued treatment effect model

Determination of the nexus between marine fishery dependence and multidimensional poverty indices can be problematic due to the non-randomness nature of the decision to participate in marine fishery. The non-randomness of marine fishery dependence could result in sample selection bias. However, this is usually addressed through matching approaches. In this regard, the treatment group is compared with the non-treatment group that has similar observable characteristics. The approach entails estimating the propensity score, $p(X_i)$ described as the conditional probability of an individual to be included in the treatment group with pre-treatment attributes X_i given. Further, propensity score matching is underpinned by the conditional independence assumption (CIA). Through this assumption, the average treatment effect on the treated (ATT) can be estimated as described in Equations (4 and 5).

$$ATT = E\left[Y_i^{\alpha} - Y_i^{n} \mid \alpha = 1, \mathrm{P}(\mathrm{X_i})\right] \tag{4}$$

$$ATT = E\left\{E\left[Y_i^{\alpha} \mid \alpha = 1, P(X_i)\right] - E\left[Y_i^{n} \mid \alpha = 0, \mathrm{p}(\mathrm{X_i}) \mid \alpha = 1\right]\right\} \tag{5}$$

Analysis of the treatment effect of marine fishery dependence using Equation (6) is only limited to binary treatment variables. Another approach that could be applied in place of propensity score matching is the endogenous switching regression (ESR). The endogenous switching regression is a popular model in impact assessment due to its strength of accounting for both observable and unobservable factors affecting outcomes and treatment assignment. However, the approach is not applicable to a multivalued treatment scenario. Further, multinomial endogenous switching regression may seem an appropriate approach in the determination of the household's decision to participate in ocean fishery and analyze its impact on different outcomes of interest. Nevertheless,

[6]The formulation is an unbiased estimate for variance; however, it does not satisfy population replication invariance (Alkire and Seth, 2014).

[7]Replication invariance states that if the deprivation score vector x' is obtained from deprivation score vector x by replicating x more than once then, $l(x') = l(x)$ (Alkire and Seth, 2014).

the approach cannot be used to estimate the average treatment effect of moving from one dependency level to another. Based on this background, the study opted for a multivalued treatment effect model because it allows for the evaluation of multivalued treatment scenario and can estimate the average treatment effect between different dependency levels. Also, the approach enables the researcher to determine the significance of moving between different dependence levels (Cattaneo, 2010).

3.6.1. Multivalued treatment effect model on the potential outcomes

To specify the ocean fishery dependence, and poverty outcomes nexus, the study followed the same framework presented by (Linden et al., 2016; Issahaku and Abdulai, 2020). In particular, let us consider units denoted as N is withdrawn from a specific large sample. In this regard, for each household i, (i = 1,…, N), the variables (Y_i, T_i, X_i) are observed. Y_i represents the vector of outcomes, T_i is a multivalued treatment variable (Relative income on ocean fishery), which takes integer values between 0 and K, while Xi, on the other hand, denotes the vector of the households' characteristics. The variable Dit, which defines the indicator of receiving treatment t for household i can be described.

$$D_{it}(T_i) = \{ \begin{matrix} 1, if\ T_i = t \\ 0, otherwise \end{matrix} \tag{6}$$

Each household, Y_{i0},…,Y_{ik}, is associated with the potential outcome. This is described in Equation (7), where Y_{it} represents the potential outcome for each household i in which T_I=t and $t \in \mathfrak{T}$ = $(0,\ldots,K)$. It is worth noting that only one of the potential outcomes will be observed in this case, depending on the dependency level. Following the framework presented by Cattaneo (2010), the observed outcome, Yi can be expressed in terms of treatment indicator D_{it} and potential outcome Y_{it}.

$$Y_i = \sum_{t=0}^{k} D_{it}(T_i) Y_{it} \tag{7}$$

Let m and l represents different treatment levels (dependence levels), such that for treatment effect δ, of treatment level m versus l can be expressed as the difference between the potential outcomes related with distinct levels.

$$\delta = E[Y_{im} - Y_{il}], \forall m, l \in \wedge \tag{8}$$

Identification of treatment effect using Equation (8) will be difficult without considering further assumptions. The reason for this is because of the non-randomness nature of the treatment assignment of the observational data associated with this study. In this regard, the multivalued treatment effect employs two assumptions; overlap assumption and conditional independence assumption (CIA). This will enable the creation of an aspect of randomness. Most importantly, conditional independence assumption (CIA) signifies that once observable pre-treatment characteristics (X_i) is controlled, the choice of ocean fishery dependence will be more of a random assignment and hence uncorrelated with the potential outcomes, which in this case are multi-dimension poverty indices as described.

$$Y_{it} \perp D_{it} \mid \mathrm{X}_{\mathrm{i}}, \forall\ t \in \wedge = \{0,...k\} \tag{9}$$

Given the covariates X_i, treatment D_{it}, and potential outcome Y_{it} are independent. The conditional independence assumption (CIA) is regarded as the strongest assumption in impact evaluation literature. The reason for this is that the assumption takes into account the unobservable confounders that simultaneously affect ocean fishery dependence and the potential welfare outcomes derived. This implies that violation of the conditional independence assumption will result in biased estimation of the effect of ocean fishery dependence on poverty and inequality. However, in the presence of sufficient data and adequately good covariates of the treatment D_{it}, one can obtain valid estimates (Issahaku and Abdulai, 2020) of average treatment effects of ocean fishery dependence on welfare outcomes.

Further, the overlap assumption is defined as; $0 < \Pr[Ti = tXi = x]$, $\forall t \in \Lambda$. The assumption ensures that each covariates X_i is associated with a positive probability of the households with similar characteristics to be selected in a particular treatment level. Conditional independence assumption and overlap assumption are jointly denoted as the ignorability assumption[8] (Cattaneo, 2010). Another assumption is the stable unit treatment value assumption (SUTVA)[9], which is also concerned with identifying average treatment effects; however, it cannot be verified from the data. Taking into account the three assumptions, one will be able to employ propensity score regression adjustment or other more robust models to estimate conditional mean function at different treatment levels. More so, observing the three assumptions will make it possible to obtain treatment effects through parametric regressions (Cattaneo, 2010).

The generalized propensity score (GPS) is preferred in this case compared to directly conditioning on X_i since it is a more practical alternative in a multivalued treatment state. In particular, the generalized propensity score entails the conditional probability of a household belonging to a specific treatment level (dependency level) given the pre-treatment covariates X_i as described;

$$r(t,x) = \Pr[T_i = tX_i = x] = \mathrm{E}[D_{it}(T_i) \mid \mathrm{X}_{\mathrm{i}} = x], \forall\ t \in \wedge \tag{10}$$

Given the characteristics of the treatment, the GPS, defined as $\hat{r}\ (t, X_i)$, can be estimated using the multinomial logit model. In this regard, it can be used to weigh observations and hence estimate average treatment effect (ATE), and potential outcome means (POM) for ocean fishery dependency levels among households with $T_i = t$ in the selected sample. For instance, application of efficiency influence function estimator, potential outcome means can be estimated as;

$$\alpha_t^{EIF} = \frac{1}{N}\sum_{i=1}^{N}\left[\frac{Y_i D_{it}(T_i)}{\hat{r}(t,X_i)} - \left(\frac{D_{il}(T_i) - \hat{r}(t,X_i)}{\hat{r}(t,X_i)}\right)\hat{Y}_i(t)\right] \tag{11}$$

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[8] Ignorability assumption implies that treatment assignment (ocean fishery dependence) is assumed to be random conditional on common support conditions and a set of observable factors (Cattaneo, 2010).

[9] SUTVA assumption requires that there should be no spillover effects from ocean fishery dependence (Cattaneo, 2010). This suggests that the welfare outcomes from an individual's dependence should be attributed to participation only and not due to the dependence of other households.

$$ATE = \left(\hat{\mu}_{EIF,m} - \hat{\mu}_{EIF,l}\right) \tag{12}$$

From the equation $r^\wedge (t, X_i)$ represents generalized propensity score and the estimated m, while $l = t$, $\forall\ t \in \Lambda$, N. is the total number of households belonging to a particular treatment level, with $T_i=l$ and $T_i=m$, $l \in \Lambda = (1, 2, 3)$. In this study, Λ =1 refers to non-ocean fishery dependence, Λ = 2 refers to low ocean fishery dependence and Λ =3 refers to high ocean fishery dependence. Moreover, $Y^\wedge (t)$ denotes estimated conditional mean functions relating to each treatment level.

Further, the quantile multivalued treatment effect was also estimated to determine the heterogeneity in ocean fishery dependence at 0.25, 0.50, and 0.75 quantiles of the distribution of potential welfare outcomes. In the estimation of both quantile treatment effect (QTE) and average treatment effect (ATE), an efficiency influence estimator (EIE) was used. The reason for this is that the efficiency influence estimator is doubly robust compared to estimators of regression adjustment (RA) and inverse probability-weighted treatment (IPW) (Cattaneo et al., 2013; Linden et al., 2016).

$$\hat{r}(x,t) = \frac{\exp\left(X_i \hat{\beta}_t\right)}{1 + \sum_{t=0}^{T} \exp\left(X_i \hat{\beta}_t\right)} \tag{13}$$

Finally, in the implementation of the multivalued treatment effect approach, the generalized propensity score was estimated using multinomial logistic regression using the three dependence level variable as the outcome as described in Equation (13), $r^\wedge(x, t)$ denotes the estimated generalized propensity score. The variables (X_i) on the right-hand side were estimated using the *bfit*[10] command present in Stata. Most importantly, the study estimated potential outcomes for each dependence level. Pairwise contrasts were also estimated between all dependence levels to find the significance of moving from one dependence level to another.

The level of ocean fishery dependence is hypothetically endogenous, and therefore, could lead to a biased estimate as a result of its correlation with the error term. That is why the study controlled for covariates X_i, including distance to the ocean fishery market and distance to the ocean fishery resource. The rationale for the variables' inclusion is that shorter distance to the fishery market reduces transaction costs and better market access, which could increase ocean fishery dependence. Further, the reduction of distance from the ocean fishery resource could also increase ocean fishery dependence due to peer influence and increased expected net economic value, which ultimately encourages the decision to participate.

3.6.2. Dose-response functions (DRF)

The generalized propensity score (GPS) was deployed to capture the association between marine fishery dependence and household welfare in a continuous treatment assignment instead of the discrete analyses (Hirano and Imbens, 2004). The analysis was taken on the households who

[10]*bfit* sub-command is used to sort fitted regression models through information criterion such as AIC or BIC and puts the best fitting model in ereturn to display ranked models in a table (Cattaneo et al., 2013).

participated in the ocean fishery and related activities. The interest of the study was to estimate the average dose-response function[11], which entails the potential welfare outcome $Y_i(t)$ of household i to specific ocean fishery dependence level t;

$$\theta(t) = E[Y_i(t)], \forall t \in \wedge \tag{14}$$

where θ is the DRF and t represents the treatment level measured as the share of ocean fishery income on the total household income. Further, the study presumed the weak un-confoundedness under the assumption that average DRF can be estimated by GPS to eliminate the selection bias (Hirano and Imbens, 2004). The assumption of un-confoundedness is usually strong but untestable. However, its plausibility is dependent on the richness of literature, particularly on the covariates determining the selection into the treatment (Hirano and Imbens, 2004; Bia and Mattei, 2008).

After GPS ($\hat{R}_i$) estimation, the conditional expectations of specific outcome variables were modeled using two scalar variables the GPS ($\hat{R}_i$): $\theta(t, r) = E[Y_i|T_i = t, \hat{R}_i = r]$ and the treatment (T_i). This was achieved using quadratic approximation (Bia and Mattei, 2012).

$$E\left[Y_i \mathrm{I} T_i = t, \hat{R}_i = r\right] = \partial_0 + \partial_1 T_i + \partial_2 T_i^2 + \partial_3 \hat{R}_i + \partial_4 \hat{R}_i^2 + \partial_5 T_i \hat{R} \tag{15}$$

The dose-response function at each treatment level t was finally estimated and averaged over the general propensity score, as shown by Equation (16). Also, confidence bounds at 95% were estimated using a bootstrapping approach (Hirano and Imbens, 2004).

$$\mu(t) = E[\theta\{t, r(t, X_i)\}] \tag{16}$$

4. Results and discussion

4.1. Descriptive statistics on ocean fishery dependency

For the purpose of this study, households who do not have income from the ocean fishery were classified as non-dependency. Low dependency referred to households with an ocean fishery dependence rate of more than 0% and less than 30%. High dependency involved households with an ocean fishery dependency rate of more than 30% (Lepcha et al., 2019). The households classified as non-dependence, low dependency, and high dependency were approximately 32.0%, 18.0%, and 50.0%, respectively.

4.2. Descriptive statistics on multidimensional poverty indices and inequality

The summary statistics for multidimensional poverty indices are presented in Table 2. The result indicated that in terms of multidimensional poverty indices, the most dependent households are

[11]Dose response function provides a graphical output of the relationship between marine fishery dependence and the potential welfare outcomes on a continuous treatment assignment.

more affected by the depth and prevalence of the household deprivation score and multidimensional poverty dummy at about 0.3, 0.5, and 0.4, respectively. More so, multidimensional poverty intensity has been observed to reduce from 0.48 to 0.47 between non-dependence and low dependence. However, the multidimensional poverty intensity increased to 0.50 when the household moved to the high dependence implying that higher dependence on fishery increases poverty. This could have been attributed to low diversification to alternative livelihood options by most households participating in ocean fishery resulting in low adaptive capacity and hence more sensitive to weather and idiosyncratic shocks. Also, a higher incidence of poverty among the dependent households could be as a result of poor financial management and a lack of sustainable land ownership rights, which contribute to low entrepreneurial activities and minimum efforts in accumulating wealth.

Table 2. Descriptive statistics of multidimensional poverty indices.

Outcome variables	Non-dependence	Low dependence	High dependence	F-statistics[12]
Household deprivation score[13]	0.2507	0.2933	0.3442	10.3000***
Multi-dimension poverty intensity[14]	0.4806	0.4714	0.5010	0.7400*
Multi-dimension poverty dummy[15]	0.2901	0.4262	0.4792	5.9700**
Number of observations	384			

Note: *significant at 10%, **significant at 5%, ***significant at 1%.

The discussion is supported by Cinner et al. (2012), who found higher level of poverty trap among fishers due to low diversification strategies attributed to marginalization and lack of social safety net, skills, contacts, and other critical resources. The higher dependence on one livelihood option that is associated with a wide range of stressors exposes households to dynamic vulnerability and hence poverty. Within this context, the natural resource is used to provide safety nets in response to shocks and gap filling of seasonal shortfalls. Using natural resource as a risk management strategy among households could lower their capacity to escape poverty. This is demonstrated by increasing multi-dimension poverty indices across the three subgroups. Another possible explanation for this could be that the root cause of poverty in the fishery is not the low productivity but an acute institutionalization, economic, and political marginalization of the fishing communities (Béné et al., 2016).

[12]The low F-values indicate that the variance of the outcome variables, particularly multidimensional poverty intensity, as explained by the dependent levels, is low. However, it represents a rare event that cannot impose any suspicion on the null hypothesis.

[13]Household deprivation score is the average deprivation scores of the households (both rich and poor) in each dependence level.

[14]Multidimensional poverty intensity entails summation of the deprivation scores of the poor divided by the number of poor people (Alkire and Santos, 2013).

[15]Multidimensional poverty dummy is the incidence or headcount ratio of multidimensional poverty (Alkire and Santos, 2013).

4.3. Inequality measure on the ocean fishery dependency

Table 3 presents the results of inequality across ocean fishery dependence levels using the separate inequality measure and positive-multiple variance. The findings indicated an increasing level of poverty and inequality with dependence levels. More specifically, non-dependence, low dependence, and high dependence levels had inequalities of approximately 0.12, 0.13, and 0.14, respectively. This suggests that higher dependence on ocean fishery and related activities has an un-equalizing effect on attaining different dimensions of human life. This could have been attributed to higher returns gained by specific households who have invested in specialist fishing. The returns accrued to these households enabled investment in various dimensions such as education, assets, health insurance, housing, and better living conditions resulting in lower deprivation scores. This could also be explained by urbanization, social network, and tourism that have exposed some dependent households to better market opportunities such as the supply of prawns and crabs in reputable hotels. Further, ocean fishery is a common pool resource; however, territorial control and privatization of productive areas have created a disparity in economic benefits gained by different households (Neiland and Béné, 2013).

Table 3. Inequality across dependency levels.

Dependence levels	Incidence (H)	MPI (M_0)	Intensity (A)	Inequality
Non-dependence	29.01%	0.1394	48.06%	0.1245
Low dependency	42.62%	0.2009	47.14%	0.1266
High dependence	47.92%	0.2401	50.10%	0.1413
Number of observations	384			

Note: Adjusted multidimensional headcount $M_0 = H \times A$ (Alkire and Suman, 2014).

Nhem et al. (2018) reported that higher inequality among natural resource-dependent households is due to weak natural resource management that results in loss of biomass. This affects the livelihood of the poor who are constrained by a lack of alternative livelihood strategies resulting in less capability and incentive to pursue other dimensions of human life. Further, fishing communities are typically considered poor (Béné and Friend, 2011; Nabi et al., 2011; Stanford et al., 2013; Jeyanthi et al., 2016; KC et al., 2019) because of socio-institutional constraints that spur vulnerability to climatic shocks. Therefore, higher inequality among ocean fishery-dependent households could have been attributed to the positive relationship between MPI and inequality, which has been reported to be higher among the poor (Alkire and Suman, 2014; Espinoza-Delgado and Klasen, 2018). Given that multidimensional poverty and material deprivation has a positive and significant relationship with income inequality (Yang and Vizard, 2017), the study also examined Gini decomposition by income sources and found that the addition of ocean fishery income in a diversified livelihood option reduced income inequality from approximately 0.48 to 0.47. Also, Results also revealed that fishing was not a choice, but rather a necessity with approximately 71.3% of the dependent households reporting lack of alternative livelihood options. More so, the dependent households that pursued diversification livelihood strategies had lower deprivation score of 0.29 compared to 0.47 that engaged solely on fishing. This implies that marine fishery has the potential to reduce poverty and inequality if supplemented with other livelihood options.

4.4. Econometric analysis on the effect of ocean fishery dependence on poverty and inequality

A diagnostic test on the existence of endogeneity was determined using Durbin-Wu-Hausman test, as indicated in Table A1. The result indicated the existence of endogeneity in a multidimensional poverty dummy at a 10% significant level. Sargan's test was also used to test whether the instruments are correlated with the error terms (Sargan, 1958); the result was Pr > $x2(1)$ = 0.281, for household deprivation score, Pr > $x2(1)$ = 0.448 for multidimensional poverty intensity and Pr > $x2(1)$ = 0.659 for multidimensional poverty dummy, This indicates that the error terms were uncorrelated with the instruments due to larger and insignificant p-values. Further, the study used the Wald test to determine the joint significance of the instrumental variables and in testing the hypothesis of weak instruments. Wald test was $x2(2)$ = 65.04 at a 1% significant level as indicated in Table A2; therefore, the hypothesis of weak instruments was rejected

To determine the marine fishery dependence, poverty and inequality nexus, the multivalued treatment effect model was determined. Firstly, multinomial logit was estimated to predict the probability of the treatment levels as a function of the covariates X_i, as shown in Table A3 in the appendix. In this sense, it is important to note that the estimators were treated as non-parametric and, as such, cannot be inferred as marginal effects (Cattaneo et al., 2013). The predicted probabilities were later tested to find out if they were less than one and greater than zero. The result indicated that the conditional densities for each dependence level showed no mass of observations with predicted probabilities close to either one or zero (Table A4). This implies that overlap condition to make parameters identifiable has been met, as shown in Figures 2, 3, and 4.

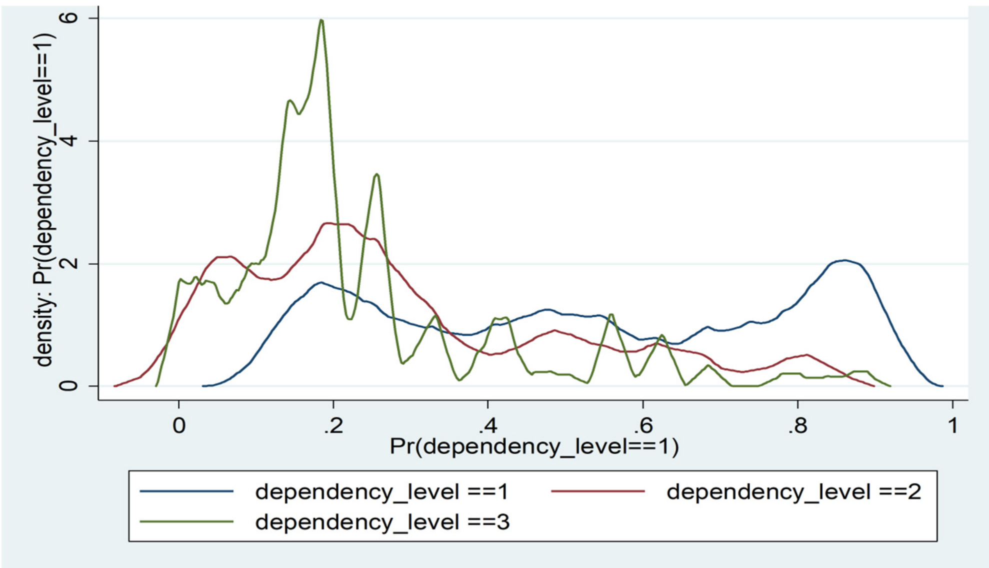

Figure 2. Conditional densities for probability of treatment on non-dependency category.

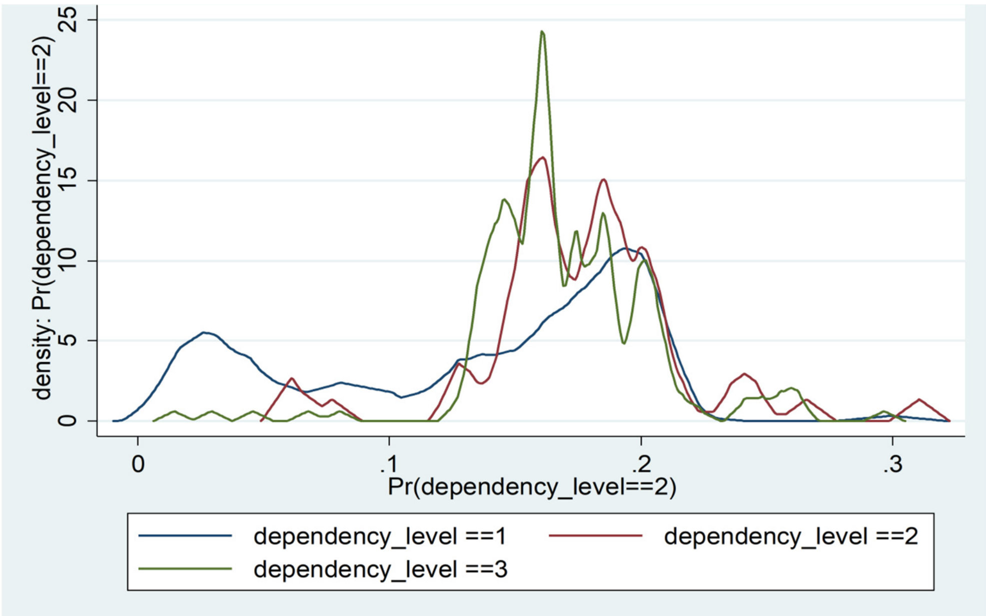

Figure 3. Conditional densities for probability of treatment on low dependency category.

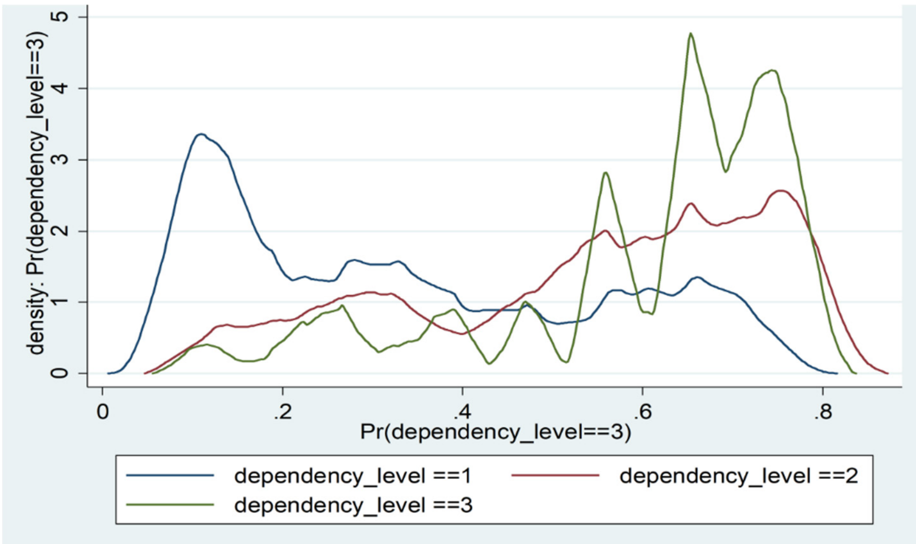

Figure 4. Conditional densities for probability of treatment on high dependency category.

Further, average treatment effects (ATE) on the levels of ocean fishery dependence on each potential welfare outcome were estimated, as presented in Table 4. The results indicated that the estimated treatment effects of moving between the different ocean fishery dependence levels were statistically significant from zero in all multidimensional poverty indices. Therefore, according to non-overlapping confidence intervals, the null hypothesis that the dependence levels have the same values will be rejected (Cattaneo, 2010). The results also revealed a consistent trend in which multidimensional poverty indices increased from non-dependence to high dependence. In particular, the increase in the household deprivation score and multidimensional poverty intensity is between 5% and 24% as the dependence level moves from the lowest to the highest. This implies that an increase in poverty is associated with higher ocean fishery dependence. Marginalization and lack of alternative livelihood options for the fishing communities impede their ability to cope with shocks and fluctuation in fishery production Cinner et al. (2011).

Table 4. Multivalued average treatment effect (ATE) of treatment level *m* relative to treatment *l* (EIE).

	Household deprivation score		Multidimensional poverty dummy		Multidimensional poverty intensity	
	ATE	Std error	ATE	Std error	ATE	Std error
Non-dependency to low dependency	0.0926***	0.0319	0.3874***	0 .0930	0.1901**	0.0454
Non-dependency to high dependency	0.1673***	0.0266	0.4618***	0.0836	0.2430***	0 .0422
Low dependency to high dependency	0.0747***	0 .0278	0.0745*	0.0693	0.0529*	0.0367
Number of observations	384					

Note: *significant at 10%, **significant at 5%, ***significant at 1%.

Even in the presence of low economic surplus, labour may still be attracted to ocean fishery in response to natural disasters. Studies done in East Africa found that fishing communities are less likely to stop fishing amid uncertainty and a decline in fish stock (Daw et al., 2012; Batista et al., 2014). The possible explanation for this is deprivation in productive assets and a lack of capacity to diversify to alternative livelihood options. Therefore, the poverty of fishing communities is associated with income and unemployment. This makes them vulnerable to social pressure and climatic shocks and hence continues to get stuck in a poverty-natural resource trap. Even though the government of Kenya has introduced co-management and fisheries development programs through its blue economy approach, lack of property rights and underperforming beach management units (BMUs) prevent poor households from achieving sustainable and resilient livelihoods.

According to Ding et al. (2017) and Ebenezer and Abbyssinia (2018), in Africa, fishery-dependent households had been found to have higher vulnerability due to limited societal capacity. Daw et al. (2012) and Beckline et al. (2018) went further to explain that even when the natural resource-dependent households have the knowledge for alternative livelihood options, they are usually constrained by socio-cultural, institutional, and economic factors. Thus, natural resource livelihood strategy remains only viable for these particular households. Failure to maintain clear and sustainable land ownership rights impedes fishers from investment in buildings and capital intensive structures. As a result, fishers could observe a rise in income but a limited increase in wealth (Fabinyi, 2019). Other studies done in Kenya and Viet Nam reported that the higher incidence of poverty in fishery emanates from exogenous source involving lack of alternatives outside the fishery, and endogenous front described by over-exploitation of fishery resource (Cinner et al., 2009; Hanh and Boonstra, 2019).

4.5. Heterogeneous treatment effect on the ocean fishery dependency

To determine the ocean fishery dependence and inequality nexus, household deprivation scores were used (Alkire and Seth, 2014; Espinoza-Delgado and Klasen, 2018) to estimate the quantile treatment effect model. The results are presented in Table 5. The percentage change was calculated by expressing the average treatment effect (ATE) as the percentage of the potential outcome means (POM) (Issahaku and Abdulai, 2020). The potential outcome means (POM) results are presented in the appendix in Table A6. The quantile treatment effect results indicated that increasing ocean fishery dependence is associated with increased household deprivation scores across all quantiles, as shown in Table 5. The higher dependence restricts both social and material well-being because returns from natural resources are extremely volatile (Edirisinghe, 2015).

Table 5. Quantile treatment effect of moving from *l* to *m* (EIE).

	Q25		Q50		Q75	
From *l to m*	QTE	% change	QTE	% change	QTE	% change
Non-dependence to low dependence	0.0000	0.00	0.0208	9.99	0.1042*	41.70
Non-dependence to high dependence	0.1250**	150.06	0.0625*	27.28	0.1667***	47.08
Low to high dependence	0.125***	60.01	0.0417*	15.40	0.0625*	15.00
Number of observations	384					

Note: *significant at 10%, **significant at 5%, ***significant at 1%.

Based on percentage terms, moving from non-dependency to high dependency was about 0%, 10%, and 42% in the 25th, 50th, and 75th quantiles of household deprivation score, respectively[16]. This increases to approximately 150%, 27%, and 47% if the household moves from non-dependency to high dependency. The results indicated heterogeneity in household deprivation scores across quantiles in all efficiency influence estimators (EIE), as shown in Table 5 and Figures 5, 6, 7, and 8. This implies that some households, particularly in the lower quantiles, benefited more from the ocean fishery compared to others due to higher investment in capital intensive fishing gears such as ring nets and sport fishing facilities. Another possible explanation for this could be as a result of constraints enumerated by dependent households such as land tenure security and access to credit that prevents them from investing in ocean fishery or even other entrepreneurial activities. Eggert et al. (2015) reported similar results in assessing the welfare effect on Lake Victoria fishery, where they found a simultaneous increase of real income with inequality. The finding suggested that growth in real income accrued to the wealthier households, with poor households having limited growth in their real income due to disparities in social and financial capital that ultimately contribute to materials deprivations.

Social struggles among the dependent households in relation to power and money have enhanced inequality (Bavinck et al., 2018). This has become evident as countries embrace the blue revolution because the ability to benefit from the ocean resource has also been transformed. The shift to high technological capability has improved fishing efficiency and enhanced capacity growth. However, disparity to technological access has further escalated inequalities among fishers. More than half of the conducted interviews indicated that access to advanced technology among the dependent households was attributed to financial capital and social connections. They further noted that fishers with advanced equipment are more likely to earn higher returns compared to those using

[16]The variance matrix estimator used 2000 bootstrap repetition in quantile treatment effect estimation (Cattaneo et al., 2013).

traditional methods such as foot fishing with lining. This implies how technology has contributed to inequality among dependent households.

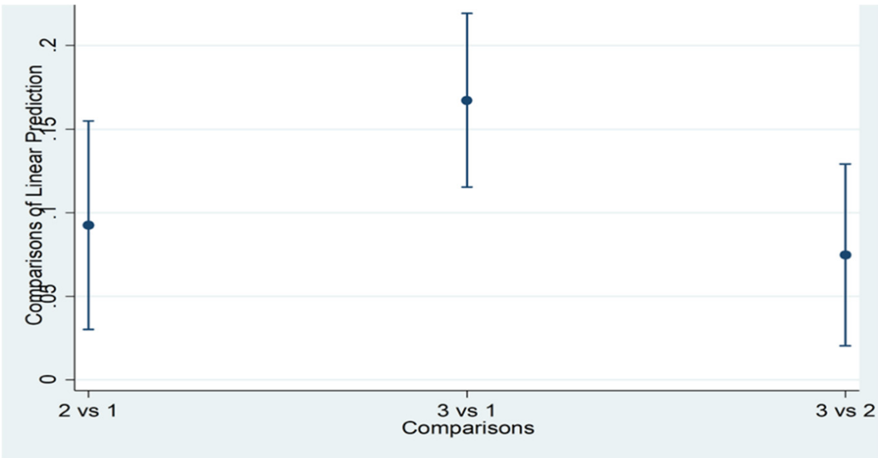

Figure 5. Full pairwise comparison of average treatment effect (ATE) with 95% Cis.

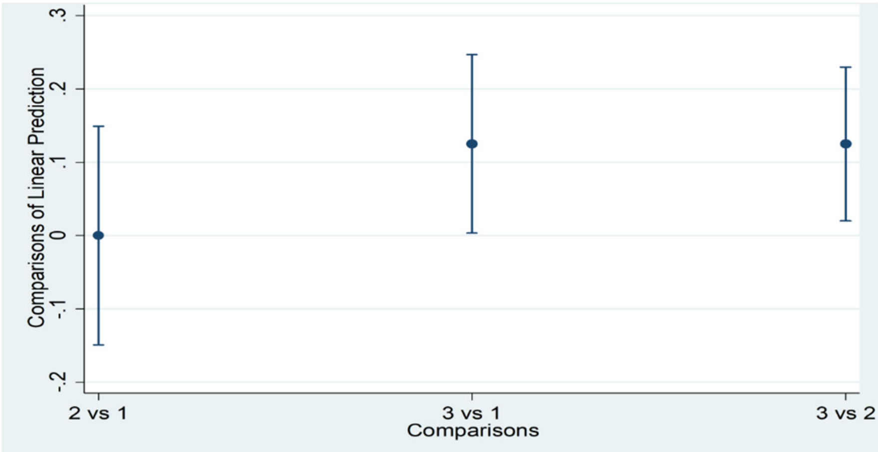

Figure 6. Average treatment effect comparisons in the 25th percentile with 95% Cis.

The margins plot for pairwise comparisons for full sample and 25th, 50th, and 75th percentile of the household deprivation score are presented in Figures 5, 6, 7, and 8, respectively. From the Figures, 2 vs 1 denotes moving from non-dependency to low dependency level, 3 vs 1 entails moving from non-dependency to high dependency, and 3 vs 2 represents moving from low dependency to high dependency. The Figures depict graphical representations of quantile treatment effect as presented and discussed in Table 5.

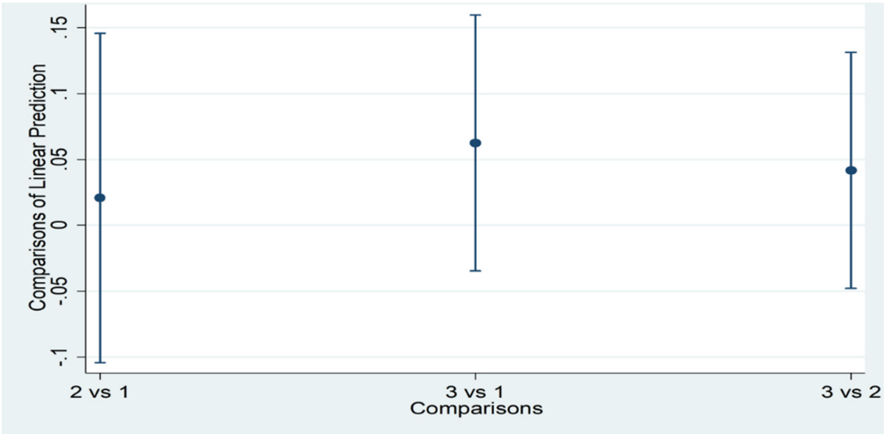

Figure 7. Average treatment effect comparisons in the 50th percentile with 95% Cis.

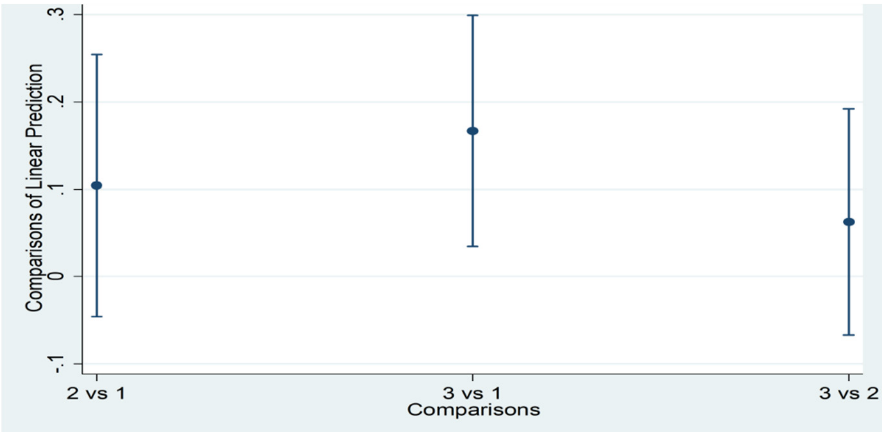

Figure 8. Average treatment effect comparisons in the 75th percentile with 95% Cis.

4.6. Dose response function

The nexus between ocean fishery dependence and poverty outcomes was also examined using the dose-response function. Out of the 384 sample, 261 households participated in ocean fishery and related activities, representing approximately 68% for which was adequately enough to provide data for estimation of dose-response function on the outcome variables. Equation (16) was used to estimate the dose-response function. However, the estimated regression coefficients were not discussed since they lack direct interpretation (Hirano and Imbens, 2004), but they are reported in the appendix section in Table A8. Further, based on the literature on the effect of natural resource dependence on poverty and inequality, the study assumed that the covariates presented in Table A7 are good predictors of the treatment levels, and hence the un-confoundedness assumption was satisfied (Issahaku and Abdulai, 2020). Also, the common support condition was met because almost all the variables in each treatment level balance out except the group membership and price since they had a *t-value* of greater than 1.282 (Bia and Mattei, 2008). The dose-response function results for multidimensional poverty intensity, household deprivation score, and per capita income are presented in Figures 9, 10, and 11, respectively.

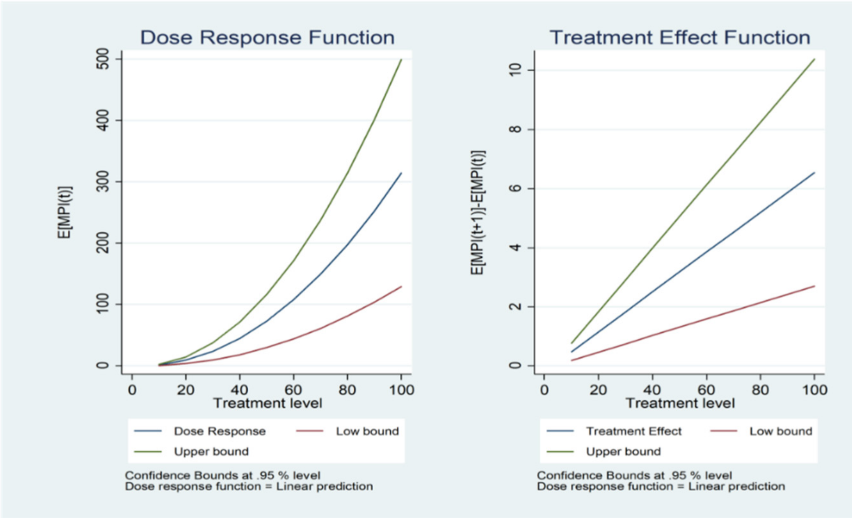

Figure 9. Dose response function and corresponding marginal treatment effect estimates on MPI.

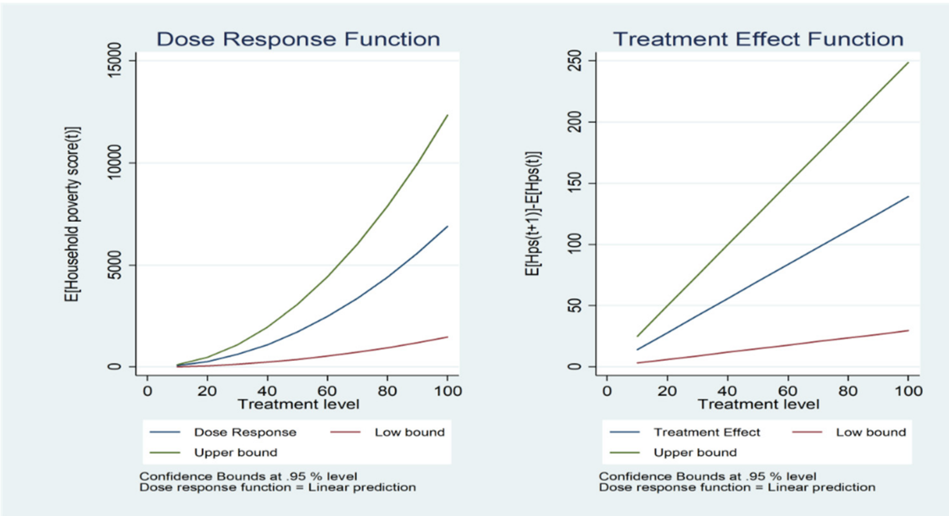

Figure 10. Dose response function and corresponding marginal treatment effect estimates on Household deprivation score.

The dose-response function results indicated a positive and linear relationship between increasing ocean fishery dependence and the poverty outcomes, as shown in Figures 9 and 10. This suggests that as ocean fishery dependence increases, the household's probability of being multi-dimensionally poor increases. The possible explanation for this is that higher dependence is mostly associated with higher climatic and idiosyncratic shocks, lower entrepreneurial behaviors, and poor access to effective fishing technology. Neiland and Béné (2013) reported that the linear relationship between poverty and fishery is attributed to institutional factors and fishing entitlement failures. Thus, the possibility of using ocean fishery as a pathway out of poverty relies not only on conserving fish stocks but also on shaping the household's command on the resources (Bosire et al., 2015). Given that ocean fishery dependence is associated with increasing income, as indicated in

Figure 11, effective management systems are critical to eliminate inequality and maximise fishing returns that will subsequently enhance food security and alleviate poverty.

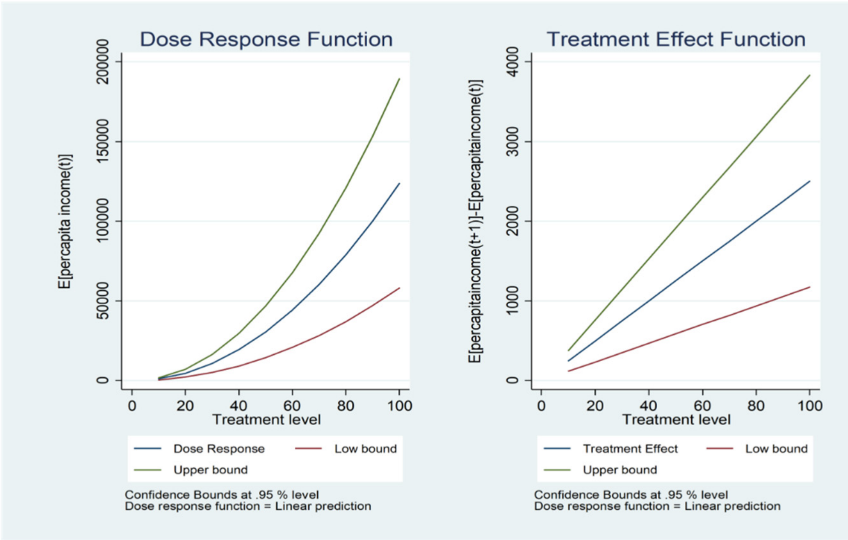

Figure 11. Dose response function and corresponding marginal treatment effect estimates on per capita income.

5. Conclusions and recommendation

This study examined marine fishery dependence, poverty, and inequality nexus in the coastal lowlands of Kenya using a multivalued treatment effect model. The results showed that higher marine fishery dependence is associated with increased poverty and inequality. The relationship between ocean fishery dependence and poverty measures appears to be linear, particularly with respect to multidimensional poverty intensity and household poverty score. In contrast, when ocean fishery income is supplemented by other livelihoods income, the results indicated a reduction in income inequality and poverty outcomes.

The findings of this study have several implications for investment and policy formulation in sustainable marine resource management to address vital welfare challenges. Firstly, the positive and linear relationship between marine fishery dependence and poverty indicated higher dependence on one livelihood option. Therefore, the Kenyan government needs to promote off-fishery employment opportunities through public investment such as infrastructural development, education on entrepreneurial activities, and creating awareness on the available jobs. This will create an enabling environment for alternative diversification options and shape the household's command of the resources critical for facilitating sustainable livelihood strategies.

Secondly, since the marine fishery is an important livelihood option, especially among poor households, the facilitation of better regulatory compliance is critical. In this regard, destructive fishing gears such as the use of trawlers as observed in Malindi (Shella Ward) should be banned. This calls for the need to strengthen existing governance options such as BMUs and LMMAs to reduce externalities, including pollution, habitat loss, and social harassment, which will ultimately promote efficient use of the marine resource.

Thirdly, the government should provide training for the fishery community on sustainable production methodologies. However, to achieve this, investment in extension personnel is important for the transfer of knowledge to these dependent households. More so, the recommendation requires an increase in capital availability to transform the training into an investment. Therefore, the government is recommended to provide financial support to the fishery community by introducing low-interest loans to the fishers. This will also provide the means for the fishers to acquire their own fishing gear, given that majority of them depend on the hired fishing equipment.

Fourthly, research and development on fishery processing should be encouraged to promote value addition in the sector. Most fishers in the coastal region of Kenya sell their catch directly to the Beach Management Units' joint marketing facilities. In this sense, there is no major fish processing technology deployed by either BMUs or the fishermen. Therefore, research and development will provide technological breakthroughs in local fish processing, which will increase earnings from the catch.

The findings of this study will be important to other countries with similar social and economic structures. More fundamentally, it will provide information on the relationship between marine fishery dependence, poverty, and inequality. As a result, they will be able to formulate welfare policies that will provide a pathway for the dependent households to escape poverty traps. It is noteworthy that although this research offers vital insight into marine fishery dependence, poverty and inequality, the data is cross-sectional and limited only to Kilifi County, Kenya. Therefore, extending temporal and spatial coverage would be important to produce more generalized findings. Also, the research was limited by poor records among households head, but it relied on thorough probing to assure the quality of data collected.

This research could be extended to involve the evaluation of the vulnerability and resilience among the ocean fishery-dependent households to climatic and idiosyncratic shocks; analysis of natural resource governance and livelihood nexus among the ocean fishery-dependent households; assessment of the barriers for alternative livelihoods among marine fishery-dependent household; determination of the drivers of marine fishery dependence and poverty outcomes; and analysis of the growth of fisheries communities along the coastal lowlands of Kenya and its effect on the marine fishery. This will help in finding the appropriate policy interventions in promoting sustainable livelihood strategies, which will alleviate poverty and inequality and contribute to the achievement of blue economy goals.

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Conflict of interest

All authors have no conflict of interest to declare in this paper.

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