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Illegal fishing and catch potentials among small scale fishers

Application of endogenous switching regression model

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Summary

Wild fish stocks are facing increasing threat of extinction partly due to the use of illegal fishing methods. In developing coastal countries where fishing activities are the mainstay of the population along the coast, livelihoods are being directly threatened. Although a number of studies unearthing factors determining supply of violation of fishing regulations exist, literature on the relationship between intrinsic catch potentials or fishing skills and illegal fishing behavior is scarce. Using data on violation of light attraction regulation among small-scale fishers in Ghana, our results show that the risk of punishment, fishing experience, skipper's age and religious norms influence the decision to violate. Most importantly, we found that violators and non-violators have different fishing kills. Specifically, violators would have higher catches than non-violators if non-violators violate too. On the other hand, if the violators had not violated, they would have obtained lower catches than their counterparts who are not in violation. Consequently policies targeting illegal fishing must, in addition to traditional variables that influence violation decision, concentrate on improving the skills of the less efficient fishers

Keywords: illegal Fishing, endogenous switching, fishing skills, Ghana

***JEL* Classification**: Q22, K42, C21

1. Introduction

According to the Organization for Economic Cooperation and Development (OECD) (2006) estimates, illegal fishing has undoubtedly contributed significantly to the world fisheries crisis. In developing coastal countries where the majority depends on fishing and related activities, food security and sustainable livelihoods are seriously threatened (Pauly and Zeller, 2003). To address illegal fishing, drivers of the supply of fishing crimes need to be clearly understood and targeted. In view of this, limited number of studies have been done and the strengths of factors such as the risk of detection, severity of punishment, rate of time preference, other socio-

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economic variables, and equity and fairness consideration have been identified (see, e.g., Furlong, 1991; Kuperan and Sutinen, 1994; Hatcher et al., 2000; Hatcher, 2005; and Chavez and Salgado, 2005; Akpalu, 2008; 2009; 2010; 2011). The theoretical foundation derives from Becker's (1968) theoretical model which views the potential criminal as a self-interested and rational economic agent who aims at maximizing expected utility from illegal fishing. Thus, the fisher engages in illegal fishing if the expected gains from violation outweigh the gains from legal fishing.

However, to the best of our knowledge, the question of whether violators and non-violators have inherent different catch potentials, all else being equal, has received very little attention. The only existing work in the fisheries economics literature relates technical efficiency to violation decisions (Akpalu, 2011). This study extends the empirical literature by estimating counterfactual catches of violators and non-violators using an endogenous switching regression model (see Heckman, 2001); and compares the estimated expected counterfactual catches of the violators to their reported average counterfactual catches. Furthermore, we investigate factors that explain why some violators overstated or understated their counterfactual catch levels relative to the estimated values. Moreover the traditional model of determinants of violation decision has also been estimated.

Data from an artisanal fishery in Ghana is used for the analysis and the illegal fishing activity considered is the use of light aggregation equipment, which involves shining light in the ocean to aggregate the stock for easy harvest. This activity has contributed to overfishing (Akpalu, 2011). Thus the main hypothesis tested in this study is whether fishers with low fishing skills are more likely than those with high skills to violate fishing regulations. The results indicate violators and non-violators have different fishing skills and therefore different catch potentials. Indeed violators will obtain higher catches than their counterparts (i.e., non-violators) had the non-violators violated the regulation. On the flip side, the non-violators would have obtained higher catches than violators, had the violators obeyed the regulation. Furthermore, violation decisions are influenced by the risk of detection, age of the skipper, the fisher's perceived rightness of the regulation, and observance of religious norms. In addition, fishing experience, perceived fairness of the regulation and the number of dependants a fisher has influences his judgement on counterfactual catch potentials.

The remainder of the manuscript is organized as follows. Section 2 presents the econometric model followed by the description of the data in section 3. Section 4 contains the empirical model and the estimation results. Section 5 concludes the paper.

2. The Econometric Model

In order to determine the counterfactual catch potentials of violators and non-violators of the fishing regulation, an endogenous switching regression model of violation decision and catch is employed. The model uses a probit model in a first stage to determine the relationship between violation decision and possible determinants of supply of violation. The second stage regression estimates the determinants of catch levels for violators and non-violators conditional on specific criterion function. To clarify the method, consider a situation where a fisher could violate the fishing regulation or not. Let $\mathrm{A}_i^* > 0$ be a latent variable capturing the expected net benefits from violating the regulation. We specify the probit model of violation of the regulation as

$$A_i^* = \mathrm{Z}_i\alpha + \eta_i \text{ with } A_i = \begin{cases} 1 & if \;\; \mathrm{A}_i^* > 0 \\ 0 & otherwise, \end{cases} \tag{1}$$

where Z_i is a vector of factors influencing decision to violate; α is a vector of unknown parameters; and η is an error term with mean zero and variance of σ_η^2. Probit maximum likelihood estimation is employed to estimate the parameters of equation 1. The decision to violate the regulation or not is influenced by catch potentials. Let the catch (production) function be $y = f\left(X\right)$, where y is catch and X is a vector of inputs. To estimate a separate regression function for each of the two situations, we specify the following production functions:

$$\text{Regime 1 } \left(\textit{Violators}\right)\text{: } y_{1i} = X_{1i}\beta_1 + \varepsilon_{1i} \quad \textit{if } A_i = 1 \tag{2a}$$

$$\text{Regime 2 } \left(\textit{Non-Violators}\right)\text{: } y_{2i} = X_{2i}\beta_2 + \varepsilon_{2i} \quad \textit{if } A_i = 0 \tag{2b}$$

Where y_{1i} and y_{2i} are catch levels of violators and non-violators respectively, and β is the vector of parameters to be estimated. The error terms in equations (1), (2a) and (2b) are assumed to have a triumvirate normal distribution with zero mean and covariant matrix Σ, (i.e., $(\eta, \varepsilon_1, \varepsilon_2) \sim N(0, \Sigma)$), with $\Sigma = \begin{bmatrix} \sigma_\eta^2 & \sigma_{\eta 1} & \sigma_{\eta 2} \\ \sigma_{1\eta} & \sigma_1^2 & . \\ \sigma_{2\eta} & . & \sigma_2^2 \end{bmatrix}$. Where σ_η^2 is the variance of the error term in the selection equation (1) which can be assumed to be equal to 1 since the coefficients are estimable only up to a scale factor (Lee, 1978; Maddala, 1983), σ_1^2 and σ_2^2 are the variances of the error terms in the productivity functions (2a) and (2b), $\sigma_{1\eta}$ represent the covariance of η_i and ε_{1i}, and $\sigma_{2\eta}$ is the covariance of η_i and ε_{2i}. Note that y_{1i} and y_{2i} are not observed simultaneously implying the covariance between ε_{1i} and ε_{2i} is not defined and therefore indicated as dots in the covariance matrix. Since the error term of the selection equation (1) is correlated with the error terms of the productivity functions (2a) and (2b), the expected values of ε_{1i} and ε_{2i} conditional on the sample selection are nonzero and are defined as:

$$E\left[\varepsilon_{1i} \middle| A_i = 1\right] = \sigma_{1\eta} \frac{\phi(Z_i\alpha)}{\Phi(Z_i\alpha)} = \sigma_{1\eta}\lambda_{1i}, \tag{3a}$$

$$E\left[\varepsilon_{2i} \middle| A_i = 0\right] = \sigma_{2\eta} \frac{\phi(Z_i\alpha)}{1 - \Phi(Z_i\alpha)} = \sigma_{2\eta}\lambda_{2i}, \tag{3b}$$

where $\phi(.)$ and $\Phi(.)$ are the standard normal probability density function and normal cumulative density function respectively, $\lambda_{1i} = \frac{\phi(Z_i\alpha)}{\Phi(Z_i\alpha)}$, and $\lambda_{2i} = \frac{\phi(Z_i\alpha)}{1-\Phi(Z_i\alpha)}$. It is noteworthy that if the estimated covariance $\hat{\sigma}_{1\eta}$ and $\hat{\sigma}_{2\eta}$ are statistically significant then the decision to violate and the quantity of fish caught per period of time are correlated. This implies there is evidence of endogenous switching and the null hypothesis of the absence of sample selectivity bias is rejected.

A more efficient method of estimating endogenous switching regression models is full information maximum likelihood (FIML) method (Lokshin and Sajaia, 2004; Greene, 2000). The logarithmic likelihood function given the previous assumptions regarding the distribution of the error terms is

$$\text{In}L_i = \sum_{i=1}^{N}\left\{A_i\left[\text{In}\phi\left(\frac{\varepsilon_{1i}}{\sigma_1}\right) - \text{In}\sigma_1 + \text{In}\Phi\left(\theta_{1i}\right)\right] + (1-A_i)\left[\text{In}\phi\left(\frac{\varepsilon_{2i}}{\sigma_2}\right) - \text{In}\sigma_2 + \text{In}(1-\Phi(\theta_{2i}))\right]\right\} \quad (4)$$

where $\theta_{ji} = \frac{\mathrm{Z_i\alpha} + \rho_j\varepsilon_{ji}/\sigma_j}{\sqrt{1-\rho_j^2}} \; \frac{1}{2}$, with $j = 1,2$, and ρ_j denoting the correlation coefficient between the error term η_i of the selection equation (1) and the error term ε_{ji} of equations (2a) and (2b), respectively.

Conditional Expectations, Treatment, and Heterogeneity Effects

The endogenous switching regression model can be used to compare observed and counterfactual catches. Thus we could compare the expected catch of the vessels that violated (i.e., (a)) with respect to fishing units that did not violate (i.e., (b)); and to investigate the expected catch in the counterfactual hypothetical cases (i.e., (c)) that the violating fishing units did not violate, and (i.e., (d)) that the non-violating fishers violated. The conditional expectations for catch productivity in the four cases are presented in Table 1 and defined as follows:

$$E(y_{1i} \mid A_i = 1) = X_{1i}\beta_1 + \sigma_{1\eta}\lambda_{1i} \tag{5a}$$

$$E(y_{2i} \mid A_i = 0) = X_{2i}\beta_2 + \sigma_{2\eta}\lambda_{2i} \tag{5b}$$

$$E(y_{2i} \mid A_i = 1) = X_{1i}\beta_2 + \sigma_{2\eta}\lambda_{1i} \tag{5c}$$

$$E(y_{1i} \mid A_i = 0) = X_{2i}\beta_1 + \sigma_{1\eta}\lambda_{2i} \tag{5d}$$

Cases (a) and (b) along the diagonal of Table 1 represent the actual expectations observed in the sample. Cases (c) and (d) represent the counterfactual expected outcomes.

Table 1. Conditional Expectations, Treatment, and Heterogeneity

Subsamples	Decision Stage: To Violate	Decision Stage: Not to Violate	Treatment Effects
Fishing Vessels that violated	(a) $E(y_{1i} \mid A_i = 1)$	(c) $E(y_{2i} \mid A_i = 1)$	TT
Fishing Vessels that did not violate	(d) $E(y_{1i} \mid A_i = 0)$	(b) $E(y_{2i} \mid A_i = 0)$	TU
Heterogeneity effects	BH_1	BH_2	TH

Note (a) and (b) represent observed expected catches per period of time, and; (c) and (d) represent counterfactual catches per period of time.
$A_i = 1$ if the fisher violated; and $A_i = 0$ if fisher did not violate
y_{1i} = Quantity of fish caught if fisher violated
y_{2i} = Quantity of fish caught if fisher did not violate
TT: the effect of the treatment (i.e. violation) on the treated group (i.e. fishers that violated);
TU: the effect of the treatment (i.e. , violation) on the untreated group (i.e., fishers that did not violate;
BH_1: the effect of base heterogeneity for fishers that violated (*i=1*), and did not violate (*i=2*)
TH= (TT-TU), i.e., transitional heterogeneity.

In addition, following Heckman *et al*, (2001) and Di Falco et al (2011) we calculate the following effects:

$$TT = E(y_{1i}|A_i = 1) - E(y_{2i}|A_i = 1) = X_{1i}(\beta_1 - \beta_2) + (\sigma_{1\eta} - \sigma_{2\eta})\lambda_{1i} \quad \text{(6a)}$$

$$TU = E(y_{1i}|A_i = 0) - E(y_{2i}|A_i = 0) = X_{2i}(\beta_1 - \beta_2) + (\sigma_{1\eta} - \sigma_{2\eta})\lambda_{2i.} \quad \text{(6b)}$$

$$BH_1 = E(y_{1i}|A_i = 1) - E(y_{1i}|A_i = 0) = (X_{1i} - X_{2i})\beta_{1i} + \sigma_{1\eta}(\lambda_{1i} - \lambda_{2i}) \quad \text{(6c)}$$

$$BH_2 = E(y_{2i}|A_i = 1) - E(y_{2i}|A_i = 0) = (X_{1i} - X_{2i})\beta_{2i} + \sigma_{2\eta}(\lambda_{1i} - \lambda_{2i}) \quad \text{(6d)}$$

(1) The treatment "to violate" on violation (TT) is the difference between (a) and (c), which is given by equation (6a); (2) The effect of the treatment on non-violation (TU), i.e., fishers who did not violate the regulation, is the difference between (d) and (b) which is given by equation (6b); (3) The effect of heterogeneity of the illegal fishers is the difference between (a) and (d); (4) The effect of base heterogeneity of fishers who decided not to violate is the difference between (a) and (d); (5) The transitional heterogeneity (TH) is obtained by comparing as the difference between (TT) and (TU). Thus we seek to determine whether the effect of violating the regulation is smaller or larger for fishers who actually violated and those who did not violate relative to their counter factual case.

3. Data description

The data for the empirical analysis came from a simple random sampling survey of 258 skippers of small-scale fishing vessels in Elmina and Cape Coast in the Central, and Axim in the Western Regions of Ghana in West Africa. The three towns are to the west of Accra, the capital of Ghana. The economies of these three areas rely heavily on fishing activities. With approval from the chief fisherman, a highly respected figure in each fishing community, a questionnaire was administered to each skipper in a face-to-face interview. The questionnaire included questions on fishing inputs such as boat size, crew size, fishing hours; subjective probability of detection, expected fine, and a choice based experimental question to estimate the rate of time preference for each respondent. Following Akpalu (2008) a five-point scale of the probability is employed: very high (0.5 or more), high (around 0.25), quite possible (around 0.10), moderately low (around 0.05), and very low (0.01 or less). To determine the individual rate of time preference, we follow the design of Akpalu (2008). The respondents were asked to choose one of two hypothetical fishery projects. One project (A) will increase the skipper's income once by an amount (X) at the end of the month in which the data were collected, but the second (B) will double the amount (2X) in six months' time. After the respondent makes his choice, he was asked to indicate the value for Project B that would make him indifferent between the two projects. This matching was used to calculate the instantaneous individual discount rate (see Akpalu, 2008 for details). The descriptive statistics of the data is presented in Table 2.

The sample is made of 47% violators and 53% non-violators. From the table, the average catch of violators, which is GH¢ 5233 (US$3737.86), is more than twice that of their counterparts who did not violate the regulation. However, the violators spent over 50% more hours fishing and have 100% bigger crew size on the average than non-violators. Secondly, while 58% of the violators perceive the light attraction regulation to be right, the corresponding figure for non-violators is 91%. Furthermore, non-violators on the average perceive the probability of detection to be slightly higher than violators, and the expected severity of punishment is much higher among non-violators than their counterparts. Finally, the violators have significantly higher rate of time preference or are more impatient than non-violators. Table 3 presents the results of the switching regression model.

Table 2. Descriptive Statistics of variables used for the regressions

	Total Sample			Violating Fishing Vessels		Non-violating Fishing Vessels	
Variable Name	**# of Obs**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Probability of detection	256	0.334	0.2	0.319	0.208	0.348	0.191
Expected fine (GH¢)	253	11.533	15.201	9.05	12.885	13.774	16.757
Regulation is right (1/ 0)	258	0.752	0.433	0.579	0.496	0.905	0.294
Skipper owned vessel(1/0)	258	0.430	0.496	0.322	0.469	0.526	0.501
Probability of violation after oath to sea-god	254	0.109	0.174	0.115	0.183	0.105	0.167
Catch (GH¢)	231	3411.86	4715.68	4868.134	5958.015	2017.29	2392.59
Fishing hours	238	85.07	110.715	98.278	137.562	76.227	75.337
Crew size	238	13.704	9.076	17.872	9.316	9.741	6.810
Boat size (in feet)	248	45.804	11.562	49.718	11.660	42.193	10.259
Age of skipper (in years)	255	38.953	12.395	35.294	10.507	42.154	13.055
Skipper's fishing Experience (in years)	256	19.957	11.628	17.942	11.005	21.735	11.910
Rate of time preference	232	160.781	108.482	182.330	118.103	142.964	96.725
Regulation is fair (1/ 0)	258	0.287	0.453	0.512	0.502	0.088	0.284
Number of dependants	246	5.724	4.137	5.513	5.032	5.915	3.120
Married (1/0)	257	0.116	0.321	0.140	0.349	0.095	0.294

Source: Primary data collected by the authors in 2010.

4. Empirical model and results

The empirical model

The empirical equations to be estimated are supply of violation function, which is a probit regression, and a catch (or production) function. The violation decision equation, which is equivalent to equation (1), is specified as:

$$Violation = f\left(prob, fine, age, fexp, rtp, own, seagod, right\right), \tag{7}$$

The dependent variable is binary taking the value 1 if the fisher violates the regulation and 0 otherwise. The explanatory variables include perceived probability of detection (or risk of detection, (*prob)*), expected fine if caught (*fine*), fishing experience (i.e., years of fishing, (*fexp*)), age of the fisher (*age*), rate of time preference (*rtp*), ownership of fishing vessel (*own*), the probability of violating after oath to sea-god (*seagod*), and perceived rightness of the regulation (*right*). Following the literature, it is expected that increased risk and severity of punishment will discourage violation; those who indicate strong commitment to the oath taken before the sea-god or think the regulation is right or have relatively high rate of time preference will be less likely to violate the regulation.

The separate catch function for violators and non-violators similar to equation (2) is as follows:

$$\ln(CATCH) = g\left(\ln\left(CREW\right), \ln\left(FEXP\right), \ln\left(HRS\right)\right) \tag{8}$$

Where ln is natural logarithm, CATCH is catch per 46-feet boat valued in Ghana Cedis (GHS), Crew is crew size, FEXP is years of fishing experience of the skipper, and HRS is hours of fishing.

Results

The second column of Table 3 denoted (1) presents the OLS results of the catch function. The Ordinary Least Square (OLS) yields biased results since it does not explicitly account for potential structural difference between violators and non-violators. The likelihood ratio test indicates that the two equations are not independent (Prob>0.00). Estimated results for the endogenous switching regressions are columns 4 and 5 (i.e., denoted (3) and (4)) in the table) respectively. The estimations were implemented in STATA using the *movestay* command (Lokshin and Sajaia, 2004). The variables included in the catch function are fishing hours, crew size, age of skipper, and fishing experience. The correlation terms ρ_i in both equations are statistically significant at 1% level indicating we fail to reject the hypothesis of sample selection bias. The parameter has alternate signs in the two equations. It has a positive sign in the equation for violators implying (1) using the illegal fishing technique significantly increases catch among violators; and (2) the violators would have had higher catch levels than non-violators had the non-violators violated the regulation. On the other hand, the parameter has a negative sign in the non-violators' equation indicating (1) without using the illegal equipment, catch levels are significantly lower among non-violators; and (2) non-violators would have had lower catch levels than violators had violators not violated the regulation. Clearly, on the average, the violators of the regulation have higher catch potential than non-violators.

With regards to the inputs, the results show only crew size is statistically significant (at 1% level) at explaining catch level among violators. The elasticity coefficient reveals catch increases by 0.7% if crew size increases by 1%. This indicates violators could potentially increase their catches by increasing the crew size. On the other hand, among the non-violators, hours of fishing, crew size, and fishing experience are statistically significant at 5% level or less in explaining catch levels. The elasticity coefficients indicate crew size has the strongest impact on catch (i.e., 0.63) and the coefficient of fishing hours is the lowest (0.33).

Table 3. Full information maximum likelihood estimate of the switching regression

	(1)	(2)	(3)	(4)
			Endogenous Switching Regression	
Model	OLS		*Violators*	*Non-violators*
Dependent Variable	Log(catch)	Violation (1/0)	Log(catch)	Log(catch)
Violate Regulation (1/0)	0.513***			
	(0.184)			
log(average fishing hours)	0.294***		0.168	0.325*
	(0.096)		(0.128)	(0.167)
Log(average crew size)	0.579***		0.703***	0.625***
	(0.139)		(0.197)	(0.200)
Log(skipper's age)	-0.701*	-1.405***	-0.346	-0.655
	(0.360)	(0.513)	(0.519)	(0.550)
Log(skipper's fishing experience)	0.293**	0.024	0.008	0.497
	(0.135)	(0.187)	(0.167)	(0.222)**
constant	6.314***	6.752***	6..040***	4.850
	(1.177)	(1.79)	(2.644)	(1..774)
Probability of detection		-1.340***		
		(0.501)		
Log(rate of time preference)		0.165		
		(0.125)		
Expected fine		-0.009		
		(0.006)		
Regulation is right (1/ 0)		-2.180***		
		(0.342)		
Skipper owned vessel (1/0)		-0.220		
		(0.206)		
Probability of violation after oath to sea-god		-2.198***		
		(0.629)		
σ_i			1.083***	1.251***
			(0.086)	(0.118)
ρ_i			0.526***	-0.755***
			(0.163)	(0.144)
Adjusted R^2	0.24			

Likelihood Ratio (LR) test of independent Equations: chi2(2) = 17.43 Prob > chi2 = 0.0016

The third column of Table 3 (i.e., marked as (2)) shows the results of the supply of violation or violation decision. The results indicate the risk of detection, perception that the regulation is right or not, skipper's age, and observance of religious norm are highly significant determinants. First, increasing surveillance (i.e., probability of detection) decreases violation rate. The computed elasticity coefficient indicates that on the average, increasing the risk of detection by 1% decreases the log of the odd ratio by 0.45%. Secondly, fishers who indicated the regulation is right are less likely to violate the regulation. Perceiving the regulation to be right decreases the odd ratio by 1.6%. Thirdly, taking an oath before the "sea-god" to obey the regulation significantly decreases violation rate. The corresponding elasticity with respect to the odd-ratio is 0.24. Finally, age of the fisher negatively influence the decision to violate, albeit nonlinearly. Increasing the age by 1% decreases the odd-ratio by 1.4%. It is noteworthy that among the significant factors, perceived rightness of the regulation has the strongest impact on the decision to violate the light attraction regulation. It follows that policy makers could direct efforts at educating the fishers about the importance of the regulation. Moreover the education may be directed to younger adults since they are more likely to violate the regulation.

Table 4. Conditional Expectations, Treatment, and Heterogeneity

	Decision Stage		**Treatment Effects**
Subsamples	**To Violate**	**Not to Violate**	
Fishing Vessels in violation	(a) 2666.20	(c) 711.04	**TT**=1955.16
Fishing Vessels not in violation	(d)1259.76	(b) 859.10	**TU**= 400.66
Heterogeneity effects	$\mathbf{BH_1}$ = 1406.44	$\mathbf{BH_2}$ = -146.06	**TH** =1554.5

Table 4 presents the results of expected catch levels of violators and non-violators of the regulation as well as their respective counterfactual catch levels. From the table, the expected catch of violators and non-violators are GH¢ 2666 and GH¢ 859 respectively. Although the figures are visibly different, it is erroneous to compare them since the two groups are inherently different. Comparing (a) and (c), clearly, the violators of the regulation would have had a significantly lower counterfactual catch levels had they not violated the regulation. Conversely, the treatment, (i.e., violation) has increased expected catch by GH¢ 1955 (275%). On the other hand, non-violators would have increased the expected catch by GH¢ 466 (47%) if they had violated the regulation. Furthermore, if both groups had violated, those violating would have had higher catches than their counterparts who are not in violation. On the other hand, if both groups do not violate the regulation, those currently violating would have had GH¢ 146 lower catch on the average compared to their counterparts who are not currently violating.

We sought to verify the relationship between the estimated counterfactual catch of violators had they not violated the regulation (i.e., (c) from Table 4) and their reported counterfactual catch. Thus, skippers who were in violation of the regulation were asked to state their catch if they had not used the light attraction equipment. Employing the Kolmogorov-Smirnov test, we found that the reported catch levels first order stochastically dominate the estimated counterfactual values at 99 percent confidence level (i.e., 0.3789 ($P > 0.000$). This indicates the reported catch levels were generally higher than the estimated values. The result from the test is confirmed by Fig. 1. The mean reported catch is GH¢ 1142, which is much higher (88%) than the estimated value of GH¢ 607. However, the correlation coefficient is positive (i.e., 0.05) but very weak. Furthermore, 55% of the violators reported a higher counterfactual catches (if they do not violate the regulation) relative to the estimated counterfactual catch levels from the regression; and the remainder (45%) reported lower catches.

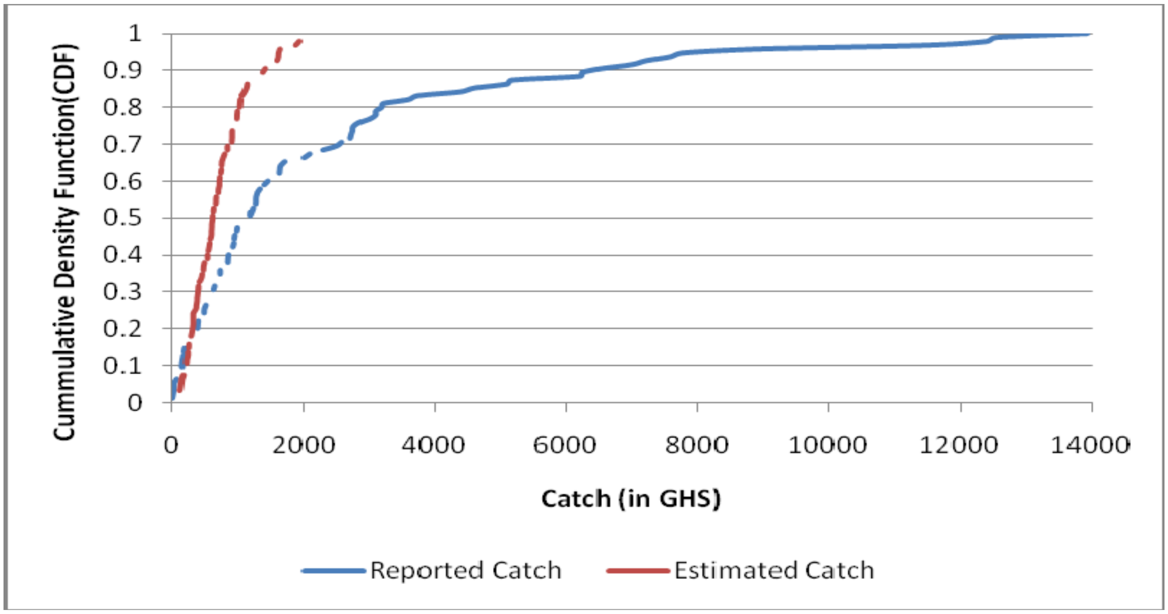

Fig. 1. Cumulative Distribution of Reported and Estimated Counterfactual Catch Levels

In addition a logit regression was estimated to further investigate possible determinants of over-reported catch levels. The results reported in Table 5 indicates that violators who had relatively more years of fishing experience were more likely to under-report counterfactual catch levels. The corresponding elasticity of the odd-ratio is -0.88. This is consistent with Eiswerth et al. (2011) which found that being familiar with an aquatic resource determine the level of awareness of the state of the resource. Secondly, among the violators, fishers who indicated that the “regulation is fair” under-reported their catch potentials. The odd ratio is 0.34 lower among those who indicated the regulation is fair. However, the fishers with relatively more dependants over-reported their counterfactual catches. The elasticity of the odd ratio with respect to this variable is 0.72. This implies fishers who are familiar with the fishery understand the stock levels are depleted and hence underestimate their catch potentials.

Table 5. Logit Regression of Determinants of Over-reported Catches of Violators

Explanatory Variables	Coefficient
Log(Fishing Experience)	**-0.878***** (0.297)
Regulation is fair (1/0)	**-0.672*** (0.407)
Number of dependants	**0.130*** (0.076)
Marital status	0.246 (0.396)
Ownership of boat (1/0)	0.731 (0.461)
Constant	**2.124***** (0.781)
Pseudo R-Squared	0.105
Number of observations	116

5. Conclusions

A number of studies have been done to unearth factors explaining supply of illegal fishing activities in developing countries. Fishers are endowed with diverse fishing skills but literature on expected and counterfactual catch differences between violators and non-violators is missing. This research has employed a switching regression analysis to estimate violation decisions as well as catch function for both categories of fishers. Also, the estimated counterfactual catch of violators is compared with stated counterfactual catches of violators to determine the accuracy of reported catch levels. Using data on artisanal fishing in Ghana, we found older fishers, those who perceived risk of detection to be high, fishers who perceive the regulation to be right, and those who have high respect for religions norms are less likely to violate the regulation.

Furthermore, based on the estimates from the endogenous switching regression model of the catch functions for the violators and non-violators, we found that the use of the illegal equipment results in higher catch among violators, and fishers who are currently violating would have higher catches than non-violators if the non-violators decided to violate the regulations too. On the other hand, if the violators did not violate the regulation, they would have had lower catch levels than non-violators. This clearly indicates violators are self selected based on their fishing capabilities. Finally, fishers were asked to state their counterfactual catch levels if they do not violate the regulation. These values were compared with the estimated counterfactual catches from the estimated model but very weak correlation was observed. Specifically approximately half of those in violation overstated their counterfactual catches. Further investigation revealed violators who perceived the regulation to be fair, those who had relatively more years of fishing experience, or have more dependants were more likely to understate their counterfactual catches. Consequently, policies aimed at addressing the illegal fishing problem should not only concentrate on the traditional variables, which include increasing probability of detection and fine, but also seek measures to improve fishing capabilities of potential violators as well as educate the fishers (especially the younger adults) on the importance of the regulation.

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