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ECONOMIC VALUATION OF ILLEGAL FISHING: AN EMPIRICAL STUDY OF BEACH SEINE BAN ENFORCEMENT IN LAKE VICTORIA KENYA

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ABSTRACT

Beach seining was banned in Kenya in 2001 largely due to growth overfishing. To date compliance with this regulation remains a challenge to managers and policy makers. This paper applies Gary Becker's model of rational criminality to examine violation of this ban in Lake Victoria Kenya using enforcement records between 2001 and 2012 with a view to identify its drivers.

Using 275 cases in Siaya, Kisumu and Homa bay counties, expected net benefit to fishing in violation of this ban was positive to both seine owners and crews (Ksh 1,079.40 and 746.75 respectively). This largely resulted from low probability of detecting (p_d=0.1390) and arresting perpetuators (p_{a_c} = 0.1136, for crew and p_{a_o}=0.2300 for seine owner). Probability of a violator being proved guilty and penalised was 0.9897 and 0.9891 respectively while average penalty was Ksh 6,769.10 with most violators paying Ksh 10,000. Court penalty to owner of seine and crew was not significantly different although expected cost was. Increasing fines could deter violation but would likely not stop it altogether even if the prescribed upper limit was applied.

Seine owners were most sensitive to p_d, p_a, revenue and cost of inputs. Improving probabilities of detecting seine owners with subsequent forfeiture of gear is most critical in enforcing this regulation. Although a hint to positive normative influence to compliance was observed, continued perpetuation of violation by few risk compromising legitimate and social concerns of those complying. Seeking these concerns alongside mechanisms that promote marginal deterrence is prescribed.

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1 INTRODUCTION

Beach seine nets have been used in fisheries for several thousand years and on every continent (Von Brandt, 1984; Gabriel *et al*. 2005). A typical beach seine is a seine net operated from the shore. The gear is composed of a bunt (bag or lose netting) and long wings often lengthened with long ropes for towing the seine to the beach. The head-rope floats on the surface, the footrope is in constant contact with the bottom and the seine is therefore a barrier which prevents the fish from escaping from the area enclosed by the net (FAO, 2011). The longer the hauling lines and the wings are the larger the fishing area that could be covered by the seine. There is no specific gear handling equipment required for fishing operations but a large number of people (depending on size of net) is needed for towing the seine to the shore. Mesh sizes for both wings and bunt as well as the height of the head-rope vary considerably and have been demonstrated to influence to a great extent the selectivity of this gear (Broadhurst & Wooden, 2007; Motlagh *et al*. 2011).
In Lake Victoria Kenya, beach seines are usually set from wooden canoes, in many cases, without engine, and then pulled from the lines simultaneously to the beach, herding the fish in front of the bag. The net wings vary in mesh size from over 250 mm but reduces towards the bunt or code-end. The code-ends are made from manila twines with mesh size less than 25 mm. Worse situations are where fishers line the code-end with smaller mesh size nets (often between 5 – 10 mm) preventing all possible escape of juvenile fish (Kariuki, 2012). Based on a 2012 Frame Survey, 73.2% of beach seines in Lake Victoria target Nile perch while about 6.3% target tilapia (Ministry of Fisheries Development in Kenya, 2012). Fishing with beach seines has become controversial over the years because of adverse impacts to the habitats and growth overfishing[1] (FAO, 2011; Malleret-King, *et al*., 2003). The use of beach seine in Lake Victoria is prohibited as a collective conservation effort among the Lake Victoria riparian states (Odada, *et al*., 2004). Case studies on fishing using beach seines in Benin, Ghana, India, Mozambique, Peru, Sri Lanka and Togo by FAO (2011) indicated that all these countries regulate beach seining.

A Lake Victoria Fisheries Frame Survey 2012 Report indicated that 1,063 beach seines operated in Kenya as of August 2012 (Ministry of Fisheries Development, 2012), which indicates that while the practice is banned, it appears to remain profitable. Studies in different fisheries have indicated low levels of compliance to fisheries regulations (Eggert & Lokino, 2008; FAO, 2011; Odada, *et al.*, 2004) which highlights the need for strong enforcement. The continued use of beach seines leaves a question as to whether or not the enforcement system is sufficient or violation too rewarding and tempting or the given the punishment for the violation is not deterrent.
This study examines the fisheries enforcement system in Kenya in a cost-benefit framework with a view of identifying the drivers critical in reducing violation of beach seining ban in Lake Victoria.

2 KENYAN FISHERIES OF LAKE VICTORIA

2.1 Fish production

From 1963 through mid-1970, fish production in Lake Victoria remained below 20,000 metric tons per year. However, this state of the fishery changed from the early 1980’s with the highest

[1] Growth overfishing occurs when fish are harvested at an average size that is smaller than the size that would produce the maximum yield per recruit.

landed volume of 200,153 metric tons in 1999. The catch for 2011 was 133,801 metric tons which earned fishers US$ 175 million based on ex-vessel prices. *Rastrineobola argentea (dagaa)*, *Lates niloticus (Nile perch)* and Tilapia are commercially important and dominant in the catch contributing 54%, 35% and 6% of the total fish catch respectively in 2011. Other species landed include *Clarias*, *Protopterus*, *Synodontis* and Haplochromines. Fish production in L. Victoria is the main fishery in Kenya and accounts for about 80-90% of the total national annual fish production (Ministry of Fisheries Development, 2011). Fisheries on Lake Victoria play a fundamental role in the country's national economy through employment creation, foreign exchange earnings, poverty reduction and food security support. It is largely artisanal thereby being a major employer and a livelihood for over 2% of Kenyans.

The trends in the fish catches over the last 13 years, however, has demonstrated a declining pattern in catches of Nile perch and tilapia species. Destructive fishing methods and increased fishing pressure on Nile perch are blamed as key contributors to this and, remain challenges to the fisheries managers and policy makers (Samoilys, *et al.*, 2011; Signa *et al*. 2008; Balirwa, *et al*., 2003).

A frame survey in 2012 showed that the fishery is operated by 40,078 fishing crews using 13,717 canoes. The dominant fishing gears were gill nets, hooks, beach seines and small seines as well as monofilament nets. 73-92% of the gill nets, long-line hooks and beach seines targeted Nile perch while small seines targeted *dagaa*. Tilapia was main target of monofilament nets, hand-line hooks and cast nets (Ministry of Fisheries Development, Kenya, 2012).

2.2 Fisheries management measures

Fisheries management measures are based on the Fisheries Act Cap 378 Laws of Kenya. It restricts fishing in fish breeding areas and during closed season, imposes limitations on fishing gears and methods as well as the restriction on size of fish to be caught, landed or traded. Fishing activities are further restricted to those with fishing licenses and must be conducted from designated fish landing stations. The gears and methods prohibited include beach seines, cast nets, monofilament nets, gill nets whose mesh sizes are below 127 mm, trawling as well as the use of explosive, poisonous or noxious substances. Before 2001, the use of beach seine for fishing was limited to those whose mesh size were 50 mm and above. This changed with enactment of Fisheries General Regulations of 2001 vide Kenya gazette notice number 7565 of 2001. Possession of beach seines in fishing area is now prohibited.

The Act prohibits catching Tilapia fish whose standard length is below 25 cm and Nile perch fish whose total length falls outside the range of 50-85 cm from L. Victoria. Landing and trading in the same is also prohibited. Whereas some of the management measures are based on scientific findings others are precautionary. The measures also take cognizance of international and regional initiatives including the United Nations Food and Agricultural organization (FAO) Code of Conduct for Responsible Fisheries (CCRF) and the Regional Plan of Actions on specific issues under the Lake Victoria Fisheries Organization (LVFO).

The Fisheries Act provides penalties for violators in form of a fine that can be as high as Kenya shillings 20,000 (US$ 250) or imprisonment of 2 years or both and possible forfeiture of item used in commission of an offense.

2.3 Enforcement of fisheries regulations

Authorized Officers for the purpose of this Act have powers to search, inspect, arrest those suspected of a violation and seize items/gear/equipment used or connected to the specific violation. The officer prefers charges against suspects in court of law for prosecution by the

State Attorney. As shown in Appendix 1, enforcement effort since 2001 has resulted in confiscation of beach seines and prosecution of violators.

The number of seines has fluctuated over time in response to enforcement efforts from 5,803 in 2000 to 553 in 2006 although there was a rise in subsequent years. The beach seines operating in L. Victoria Kenya as at August 2012 was 1,063, a figure higher than 991 and 762 observed during the frame surveys of 2010 and 2008 respectively. This seems to evidence a typical scenario of response of violators to imperfectly enforced regulations as discussed by Anthony *et al*. (1999).

The enforcement efforts have paralleled co-management efforts both regionally through LVFO and nationally. It has faced a number of challenges ranging from lack of regular presence at fishing ground, considerably low penalties to the violators, to fishers investing on arrest avoidance techniques with recent advancements in mobile telephony being a major boost to violators. Nyeko *et al.* (2009) further indicated that fishers made the beach seines in their backyards making controls from source complicated. The beach seines have also evolved from large bulky less portable forms to those that can easily be dismantled and hidden in short notice to avoid arrest. Continued use of beach seines even after imposing the ban has drawn mixed reactions which Odada *et al.* (2004) blame on failure in monitoring and enforcement.

2.4 Environmental impact of beach seining

All fishing methods impacts on environment not just targeted fish stocks but also other species, sensitive habitats, and the food chain that need to be maintained in an effort of keeping aquatic environments healthy and productive. Some standard fishing gear could be used in ways which damage the resource or the environment to such an extent that they could be considered as destructive gear. This is the case with beach seining (Odada *et al.* 2004; Kariuki, 2012) which has come under intense criticism in recent years by resource managers, policy makers and environmentalists (EAF-Nansen Project, 2010).

This criticism has largely been due to degrading effects on habitats, conflict between resource users, and the non-selective nature of beach seining techniques, which tend to result high quantities of by-catch (EAF-Nansen Project, 2010; McClanahan, 2007; King, 2000; Rubens, 1996; Malleret-King, *et al*., 2003). The impacts of beach seining are complex, hard to measure and vary from one fishery to the next (Hiddink *et al*., 2006). The areas targeted by beach seining have been reported to play a critical role as spawning and nursery grounds for many fish species. During operation, the gear churns the seabed thereby interfering with breeding fish. Given the non-selective nature of gear coupled with area where it is operated, this gear results in large amounts of juvenile catch (Njiru, *et al*., 2009; FAO, 2011; Balirwa, *et al*., 2003). The seine net scoops up other types of aquatic life which tend not to survive the experience. Beach seining has received much attention in Kenya and remains one of the primary priority issues for fisheries management (Odada *et al*., 2004; Signa *et al*. 2008).

During a study on the impact of artisanal fishing gear on coral reef ecosystem in the Southern Kenya, Mangi and Robert (2006) observed that over 68% of fish catch from beach seine were juvenile. They further reported significantly lower coral density in areas where beach seining were used deducing possible impacts of this gear. This concurs with observations by Samoilys *et al.* (2011). Case studies in a number of countries by FAO (2011), further confirmed this high level of juvenile fish in catches from beach seines. Motlagh (2011) and, Wooden *et al*. (2010) demonstrated that reduction of beach seine height and increasing mesh size could significantly reduce amount of by-catch in the catches. Mangi and Robert (2006) and Samoilys *et al.* (2011) singled beach seines as the most destructive gear in Kenya’s near-shore coastal waters emphasizing the need to enforce restrictions. Work by Odada *et al.* (2004) in L. Victoria pointed implicated the policy of free and unrestricted access to the L. Victoria fisheries as a major loophole exploited by the rent-seekers.

A survey by Signa *et al*. (2008) at the Kenya's marine coast and L. Victoria on ban of beach seineing indicated that over 80% of fishers interviewed acknowledged the existence of regulations governing the use of the beach seines. The primary reasons given by fishers for the ban were the damage caused on fish habitats (45%), the use of fine mesh size which captures juveniles (17%), overexploitation of fish stocks (7%) with 3% of interviewees having no idea about its objective which confirms earlier report by Odada *et al.* (2004).

2.5 Socio-economic aspects of beach seining

Beach seines had direct and immediate economic returns given its high efficiency and non-selective nature (Signa *et al*. 2008). As a labor intensive practice, beach seining attracts large number of crews including women and children thereby being a major employer. This concurs with observation in neighboring countries such as Mozambique (Wilson, 2012).

In the case of L. Victoria, Kenya, the Nile perch within slot size finds market in fish processing and exporting factories while large sized tilapia readily find their way to distant markets fresh after landing. This marketing structure leaves out large quantities of juvenile fish - both Nile perch and tilapia which do not meet the demands of the factories and distant markets traders. This large quantity of juvenile fish from beach seine catches supports series of other activities related to both artisanal processing as well as auxiliary services in fishing communities (FAO, 2011; Wilson, 2012).
Odada *et al.* (2004) categorised beach seines among the four major gears in Kenyan L. Victoria and the second largest contributor to landed fish by weight in 1997 after mosquitor seines, though as Malleret-King, *et al*., (2003) describes they are one of the most destructive gear types used in Kenya.

3 ECONOMIC THEORY OF LAW ENFORCEMENT

3.1 Gary Becker's model of rational criminality

This study is based on Gary Becker's model of rational criminality (Becker, 1968) which looks at criminals as rational individuals, and like anyone else, seeks to maximize their own well-being, but through illegal instead of legal means. This is seen as the monitory gain resulting from the violation.
Costs of crime can be viewed both in terms of cost forgone in committing a violation and the penalty if arrested. Opportunity forgone may take various forms, from loss of money that could have been earned through lawful means to loss of status resulting from such criminal behavior. The penalties equally vary from simple probation to fines or imprisonment. In understanding criminal behavior, Becker points out the need to recognize that there are benefits associated with crime which, for some people, are an important driver to criminal behavior. In view of this, violations will only occur if their expected net benefit to the perpetrator is positive. From this perspective, crime is seen to respond to economic conditions and incentives, and that a criminal simply chooses crime because it is the easiest job for the criminal that yields the most profit. In decreasing the profits of a crime, the motivation to pursue that line of crime decreases as well. On the same note, the number of offences is assumed to decrease as both the level of punishment and the probability of prosecution and conviction increases. The literature uses economic theory to analyze how governments should choose enforcement levels (and thereby detection probabilities) and measures of punishment in order to maximize a social welfare function.
The main assumption in Becker's paper can be expressed as follows:

$$E(U) = \theta U(B-f) + (1-\theta)U(B)$$

where U and $E(U)$ are utility and expected utility, respectively, the probability of apprehension and conviction is denoted by θ, the income if undetected is B, and the income if detected is $(B-f)$. The expected utility to an offender is seen as decreasing in θ and f. This model is supported by the fact that crime is risky and the agent will accept the gamble only if the expected utility is high enough. If people are risk averse, an increase in the probability of conviction would reduce offenders expected utility. Hence, increased probability of conviction has a greater effect than reduced penalties in the case of risk aversion

Becker uses his model, *inter alia*, to discuss how different types of punishment affect the optimal levels of enforcement and punishment; from fines, which can be imposed on the offender at a social cost close to zero, to imprisonment, torture, etc. that come at a social cost that can be even higher than the cost to the offender. Since fines are socially cheaper than other forms of sanctioning, fines are preferable as a means of deterrence. On this basis, many experts point out that imprisonment should be used only where the offenders cannot pay the full fine (Coelho *et al*. 2008; Polinsky & Shavell, 1984).

This approach to crime and punishment has been criticized particularly on the notion of rational utility maximizing agents and the lack of focus on other factors like social and moral norms. In response to this, economists have also introduced normative factors into the models of law enforcement as extensions to this Basic Model. Although the economic theory of law and enforcement has grown significantly since 1968, Gary Becker's model continues to form the foundation in the study of crime and punishment (Garoupa, 1997; Polinsky & Shavell, 2000; Polinsky & Shavell, 2006).

Stigler (1970) introduced the concept of marginal deterrence and explains that a marginal deterrence occurs when a more severe offence is deterred because its punishment exceeds that of a less severe offence. This is highly relevant under circumstances in which people can choose between committing several harmful acts, e.g. using poisonous or noxious substance to kill fish and fishing using undersize gill net. In this context, sanctions not only influence whether individuals commit offences, but also which harmful acts are chosen. All else being equal, it is socially preferable that enforcement policies create marginal deterrence so that the offences that are committed are the less harmful ones. Many others have elaborated on the issue of marginal deterrence since the work of Stigler (1970) (Shavell, 1992; Mookherjee & Png, 1994; Wilde, 1992).

3.2 Extensions to Gary Becker's model of rational criminality

Agents can engage in activities that reduce the probability of apprehension and conviction. Such activities are often referred to as avoidance activities. Among several studies focusing on this is Malik (1990), who analyses optimal enforcement when agents engage in socially costly activities that reduce the probability of being fined. This can be any activity varying from investing in technology to increase the likelihood of getting away with a harmful act, to lobbying politicians to relax enforcement in certain areas. Malik assumes that the probability of being captured and fined is a function of the agent's expenses on avoidance and enforcement expenses. Polinsky and Shavell (2001) also studied the use of bribes paid by a violator to an enforcement agent in order to avoid or reduce penalties, and extortion. Kaplow and Shavell (1994) and Polinsky and Shavell (1984) made further extensions of the basic model to allow self-reporting by the offender noting that fine for an agent who self-reports can be set below the expected fine without self-reporting. Sykes (1981, 1984) and Newman and Wright (1990) analyzed allocation of penalties with regard to crimes committed by agents on behalf of their principles.

From the Basic Model, Coelho *et al*. (2008) and Sutinen & Andersen (1985) published studies on economic analysis of illegal fishing and fisheries law enforcement respectively, where they applied Becker's (1968) model to analyze regulatory compliance in fisheries expressing the Expected profits for a firm harvesting in violation with regulations ($q > \bar{q}$) as:

$$\theta\left[\pi(q,x) - f(q-\bar{q})\right] + (1-\theta)\pi(q,x)$$

Where θ is the probability of detection and conviction, q and x are catch rate (regulated variable) and fish stock, respectively, $\pi(\cdot)$ are operating profits, and $f(\cdot)$ is the fine if convicted of a violation, with an upper bound equal to the assets of the firm. As a basis for his empirical study of deterrence in fisheries, Furlong (1991) fragmented the probability of detection and conviction θ into the probability of detection, and several conditional probabilities; prosecution given detection, conviction given prosecution, and punishment given conviction, and used this to estimate the supply of violations based on data on fishermen.

4 METHODOLOGY

This project focuses on 324 fish landing sites in L. Victoria Kenya, which administratively fall in five counties, namely Busia, Siaya, Kisumu, Homa bay and Migori. As illustrated in Figure 1, Siaya, Kisumu and Homa bay counties accounts for over 80% of the fishery of L. Victoria Kenya. Fisheries law enforcement in these counties largely rely on law courts of Bondo (Siaya county), Winam (Kisumu) and Homa bay for prosecution of those suspected of violating fisheries regulations. The Kenya Gazette notice number 7565 of 2001 was used to derive violations with regard to beach seining as follows;

i. Fishing using a beach seine in Kenya fishery waters
ii. Possession of beach seine in fishing area

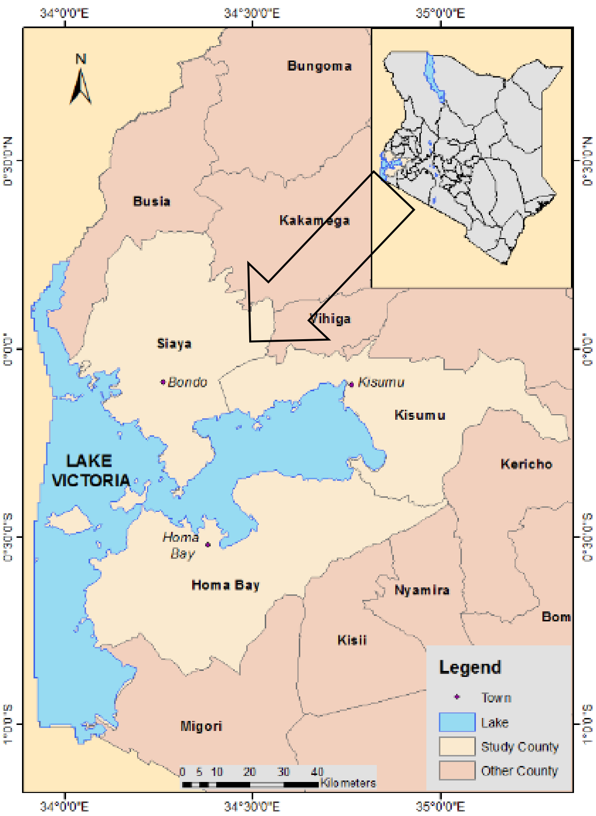


Figure 1: Map of L. Victoria Kenya showing counties of Siaya, Kisumu and Homa bay

4.1 Computation of expected benefits from violation - $\boldsymbol{\pi_{bs}}$

Expected benefits from beach seining was equated to the money value catch of resulting from one day's operation if not arrested and calculated as a function of quantity of fish caught and price. Denoting the violation, beach seining, as *bs*, this can be expressed as

$$\pi_{bs} = \varphi_{bs} * (1 - p_a)$$

Where;

Total revenue $(\varphi_{bs}) = \sum (q_1 p_1 + q_2 p_2 + \cdots + q_n p_n)$

q_1, q_2, q_n - quantities of fish species *1, 2, ...n* landed

p_1, p_2, p_n- price of fish (in Kenya shillings) per kg of species landed

p_a– the probability of violator being arrested

This study assumes that a group of eight people operate a beach seine and that they directly benefit from 30% of the proceeds of a day's seining operation which they share out equally amongst themselves. The owner of the net therefore benefits from 70% of the total proceeds. Fish price was computed from Annual statistical bulletins (Ministry of Fisheries Development-Bulletin 2008, 2011). Mean fish price of Ksh 150.48 and Ksh 129.45 for Nile perch and Tilapia respectively. Fish landing from beach seining is taken as 140 kg for Nile perch and 20 kg for tilapia per seine per day over this period of study[2].

4.2 Computation of Expected benefits to violator ($\boldsymbol{\pi_{bs}}$)

The expected benefits to each violator per incident was computed as follows

$$\pi_{bs\_c} = \frac{(30\% * \varphi_{bs})}{C} * (1 - p_{a\_c}) \qquad \textbf{for crew}$$

$$\pi_{bs\_o} = (70\% * \varphi_{bs}) * (1 - p_{a\_o}) \qquad \textbf{for owner of beach seine}$$

Where;

$C -$ number of crews operating a beach seine

p_{a_c} and p_{a_o} are probabilities of beach seine crew and beach seine owner being arrested respectively having been detected.

4.3 Computation of expected cost of violation ($\in_{\mathbf{bs}}$)

The $\in_{bs}$ was assessed in terms of penalties to the violator in court of law, having been detected doing a violation, arrested and proved guilty as described by (Eggert & Lokino, 2008). This is given as

$\in_{bs}$ =

p_d(detection)*p_a(arrested | detected)*p_g(guilty | arrested)*p_p(penalty | guilty)*penalty

Where:

p_d(detection) – probability of being detected doing a violation

p_a(arrested | detected) – probability of being arrested having been detected

p_g(guilty | arrested) – probability of being proved guilty having been arrested

p_p(penalty | guilty): probability of being penalized having been proved guilty

Penalty: conviction (fines, jail term or community service order)

[2] Computed from personal communication with BMU County chairpersons Homa Bay, Siaya & Kisumu

4.4 Computation of detection and conviction probabilities

4.4.1 *Probability of detecting beach seining ban violation (p_d)*

Records of beach seines seized during enforcement of the ban between 2004 and 2010 (appendix 1) and those observed during frame surveys over the same period were used to compute probability of detecting violators of the ban. Frame survey figures were raised by 0.3 to take care of those beach seines in fishing areas but not in operation, thus not captured by the surveys. Enforcement targets the gears in operation as well as those withdrawn from operation but is in the fishing areas (violation ii). The p_d was computed as;

$$Mean\ pd = \frac{1}{n} * \sum \frac{B_s}{B_e * (1 + r)}$$

Where:

B_s − number of beach seines seized
B_e − number of beach seines enumerated during frame survey
r − proportion of number of bs in fishing area but not operating during frame survey
n − number of years

4.4.2 *Probability of violator being arrested (p_a)*

Probability of arresting suspect/ seizing gear was conditional to detection (p_d). Data on enforcement operations (appendix 1) was used to compute the probability of arrest. This based on the number of suspects per violator category and number of beach seines seized during each quarter in a financial year computed as;

$$P_{a\_c} = \frac{\delta}{\beta * C} \quad \text{for crew}$$

$$P_{a\_o} = \frac{\varpi}{\beta} \quad \textbf{for owner of seine}$$

δ − Total number of beach seine crews arrested over a period
β − Total number of beach seines seized over the same period
ϖ − Total number of beach seine owners arrested over a period

The overall mean for this period was used p_{a_c} and p_{a_o} values for years where data was missing.

4.4.3 *Probabilities of suspect being proved guilty (p_g) and being penalized (p_p)*

Probability of being proven guilty was used to assess the strength of prosecution of cases of beach seine ban violation in court of law. On production of arrested suspect before the court, the suspect may be proved guilty or not. If proved guilty, a convict may be penalized, the severity of which is dependent on presiding court. A total of 272 records of cases of beach seine violations for a period between 2001 and 2012 were used to compute these probabilities as follows;

$$p_g = \frac{g}{a} \text{ and}$$

$$p_p = \frac{p}{g}$$

where;

g – total number of suspects proved guilty of a violation over a period
a – total number of suspects arraigned in court over same violation and period

p – total number of convicts of a violation penalized over a period

4.4.4 Court penalty for violation

Fisheries Act cap 378 Laws of Kenya against which prosecutions of these violations are made provides for penalty of *fine not exceeding Ksh 20,000 or two years imprisonment or both* but subject to presiding court. Using the data on 272 cases of violation of this ban, the mean overall penalty was calculated and compared between the counties and violation categories. Each day of community service order per convict was valued at Ksh 250.00, where this was applicable, basing on rates for unskilled labor under Government *Kazi Kwa Vijana* initiative.

4.4.5 Expected cost of violating ban on beach seining ($\in_{bs}$)

The $\in_{\boldsymbol{bs}}$ having been detected, arrested and proved guilty in court of law is a function of the penalty in terms of fine (f) or community service order and value of beach seine at time of detection if forfeited upon conviction. This was computed for each violator and compared across violation category; whether a beach seine crew or owner of beach seine, and counties. This is expressed as;

$$\in_{bs\_c} = \boldsymbol{p_d * (p_{a\_c} * p_g * p_p) * f} \qquad \textbf{for crew}$$
$$\in_{\boldsymbol{bs\_o}} = \boldsymbol{p_d} * \left(\boldsymbol{Value_{bs}} + \left(\boldsymbol{p_{a\_o}} * \boldsymbol{p_g} * \boldsymbol{p_p}\right)\right) * \boldsymbol{f} \qquad \textbf{for owner of beach seine}$$

Value of beach seine at time of detection is a function of its value when new, how long it has been in operation (p_d) and depreciation rate. The average time a beach seine is in operation depends on the probability of being detected, p_d, since the seine is confiscated if detected. The higher the probability the shorter the time the owner can expect to operate the seine before being detected. The life expectancy of a random seine is therefore likely to follow a negative binomial distribution, measuring the probability of surviving a series of random trials with success. Assuming that the value of a seine at time *t* can be approximated using relative depreciation of the form, where *V(0)* is the value of a new seine and *r* is the rate of depreciation. Obviously this is a non-linear function of time. The expected net benefit of a random beach seine is therefore the expected net benefits of a function of a negative binomial variable with one allowed failure. This is given by:

$$E(C_{bs}) = \sum_{t=0}^{\infty} \left[\frac{C_{bs}}{(1+r)^t} p_d (1-p_d)^t\right]$$

$$E(C_{bs}) = C_{bs} P_d \sum_{t=0}^{\infty} \left[\left(\frac{1-p_d}{1+r}\right)^t\right]$$

But since the denominator in the sum is bigger than one and the nominator is smaller than one, the sum is convergent and the rule of infinite sums of geometric series applies resulting in:

$$Value_{bs} = V_{(0)} * \frac{p_d}{\left[1 - \frac{(1-p_d)}{(1+r)}\right]}$$

$V_{(0)}$ and *r* were taken to be Ksh 150,000 and 15% respectively[3].

[3] Informed by personal communication with BMU chairpersons Siaya, Kisumu and Homa bay Counties

4.4.6 *Expected net benefit of violating ban on beach seining* (ν_{bs})

The expected net benefit was computed as function of outcome x(i) and the probability of such outcome p(i), expressed as Σ_i x(i)·p(i). Based on Gary Becker's model, the expected net benefits of violation of beach seine ban is expressed as

$$\nu_{bs} = \pi_{bs} - \in_{bs}$$

This was computed for each case (n=272) and compared by counties and violator category at 5% level of significance. Analysis was done to identify enforcement variables to which the expected net benefit is most sensitive.

5 RESULTS

5.1 Expected benefits from violation ($\boldsymbol{\pi_{bs}}$)

The mean π_{bs} to beach seine operators (both owners and crews) from a single day's operation if not arrested was Ksh 4,676.84 ± 350.36 with Ksh 815.83 being most common. Differences were however observed in the expected benefits to the violators between the counties and violator category. The mean difference between the π_{bs_c} and π_{bs_o} across the counties was Ksh 12,025.16. Consideration by counties across violator category showed a mean highest π_{bs} of Ksh 4,351.12 ± 599.43 (n=100) in Homa bay county. This was Ksh 1,123.02 ± 198.44 (n=99) and Ksh 9,942.59 ± 589.06 (n=73) in Siaya and Kisumu counties respectively.

5.1.1 *Expected benefit to each crew member* (π_{bs_c})

Overall, the mean expected benefits to crews was Ksh 786.34 ± 4.87 (n=184) with most crews getting Ksh 815.83 if not arrested. There was significant difference among the counties. Crews that operated in Homa bay county realized the highest mean $\boldsymbol{\pi_{bs\_c}}$ of Ksh 815.83 ± 1.33E-13 (n=74). Mean $\boldsymbol{\pi_{bs\_c}}$ in Siaya and Kisumu counties were Ksh 776.13 ± 6.68 (n=96) and Ksh 700.51 ± 34.41 (n=14) respectively. The most frequent $\boldsymbol{\pi_{bs\_c}}$ was Ksh 815.83 in Homa bay but Ksh 788.54 and Ksh 558.55 in Siaya and Kisumu counties respectively.

5.1.2 *Expected benefits to beach seine owner* (π_{bs_o})

The mean $\boldsymbol{\pi_{bs\_o}}$ across counties was Ksh 12,811.51 ± 239.49 (n=88) with most beach seine owners expecting Ksh 14,413.08. Significant differences between the counties was observed with those in Homa bay county expecting the highest $\boldsymbol{\pi_{bs\_o}}$ of 14,413.08 ± 3.638E-13 (n=26) if not arrested. This was Ksh 12,223.57 ± 270.47 (n=3) and Ksh 12,135.62 ± 317.05 (n=59) in Siaya and Kisumu counties respectively. Most beach seine owners in Kisumu and Homa bay expected Ksh 14,413.08 from every day's beach seining operation if not arrested.

Although this model used mean prices, quantities and species of fish landed, it is necessary to acknowledge that real-time values varied over the years and could influenced by a wide range of factors.

5.2 Expected cost of violating ban on beach seining ($\in_{\mathbf{bs}}$)

The overall $\in_{bs}$ across the three counties was Ksh 3,844.19 ± 331.44 (n=272) with Ksh 11,706.65 being the most common cost expected to the violator.

Comparative analysis by counties showed significant differences between the counties. It was cheaper violating the beach seine ban in Siaya county where the expected cost of violation was Ksh 397.37 ± 201.07, n=99). Expected cost of same violation was Ksh 3,093.93 ± 511.77 (n=100) in Homa bay and Ksh 9,546.44 ± 535.30 (n=73) in Kisumu county. Further significant differences in $\in_{bs}$ were observed between violator categories with mean difference of Ksh 11,660.36.

5.2.1 Expected cost of violating the ban by crews ($\in_{bs\_c}$)

The mean $\in_{bs\_c}$ for crews was Ksh 71.72 ± 5.38 (n=184) with 83.73 being most common. This was significantly different between the counties ($p<5\%$). The $\in_{bs\_c}$ of fishing using beach seine was Ksh 45.60+-4.60(n=96) in Siaya County over this period but Ksh 75.75 ± 4.45 (n=74) and Ksh 229.55 ± 37.83 (n=14) in Homa Bay and Kisumu respectively over the same period.

5.2.2 Expected cost of violating the ban by beach seine owners ($\in_{bs\_o}$)

Based on 88 cases, the mean $\in_{bs\_o}$ was Ksh 11,732.08 ± 18.19 with Ksh 11,706.64 being the most common. This was Ksh 11,654.16 ± 70.15, n=3 in Siaya county, but Ksh 11,757.18 ± 25.54 (n=59) and 11,684.13 ± 15.52 (n=26) in Kisumu and Homa bay counties respectively. The most common value of $\in_{bs\_o}$ to those convicted of possession of beach seine was 11,706.64 in Kisumu and Homa Bay counties. The observed difference between the counties was however not statistically significant.

5.2.3 Probabilities of detection, arrest, conviction and penalty

Mean probability of detecting the violation was 0.1390. This was highest in between 2005 and 2006 (p_d=0.2900) but lowest between 2008 and 2009 (p_d=0.0314). Table 1 presents summary of probabilities violator being arrested, proved guilty and penalized.

Table 1: Summary table of probabilities of arrest, proving guilty and being penalized.

	p_{a_c}	p_{a_o}	p_g	p_p
Mean	0.1136	0.2263	0.9897	0.9891
Standard Error	0.0055	0.0145	0.0103	0.0333
Mode	0.0803	0.1296	1.0000	1.0000
Minimum	0.0131	0.0690	0.7000	0.0000
Maximum	0.3704	0.5294	1.0000	1.0000
Count	184	88	272	272
Confidence Level (95.0%)	0.0108	0.0287	0.0212	0.0682

As shown in Figure 2, the highest mean p_{a_c} was attained during 2005/06 financial year (p_{a_c}=0.1886) and lowest mean probability of 0.0718 during the year 2007/08. On the other hand, the highest mean p_{a_o} was 0.3021 attained in 2009/2010 financial year.

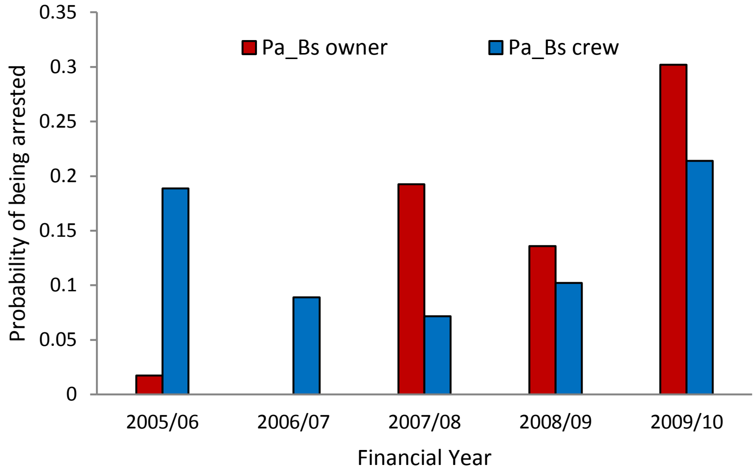


Figure 2: Trend of violator's probability of being arrested

5.2.4 Court penalty for violation

The mean overall penalty for those convicted was fine of Ksh 6,769.13 ± 299.62 (n=272) with the most common being Ksh 10,000. However, a significant difference was observed in the penalties between the three counties. Violating ban on beach seining earned a mean penalty of Ksh 4,035.35 ± 413.52, (n=99), in Siaya county where this violation was cheapest for the period covered by this study. The mean penalty were Ksh 7,461.64 ± 413.52 (n=73), and 8,970.02 ± 413.52 (n=100), in Kisumu and Homa Bay respectively. The most common penalties were Ksh 3,000 (n=99) in Siaya, Ksh 10,000 (n=73) in Kisumu county and Ksh 10,000 (n=100) in Homa bay county.

Analysis by violator category showed a mean penalty to crew fishing using beach seine as Ksh 6,620.92 ± 370.62, (n=184) with the most common being Ksh 3,000.00. This was higher for the case of the owner of seine - Ksh 7,079.00 ± 508.49 (n=88) with most common fine being Ksh 10,000.00. This difference in penalties between seine owner and fishing crew was however not significant. There were no convictions penalized by both fine and imprisonment on beach seine ban violation over this period.

5.3 Expected net benefits of violating ban ($\mathbf{v_{bs}}$)

The mean v_{bs} across the counties and violator categories was Ksh 854.39 ± 80.67 (n=272). Although a significant differences in v_{bs} between counties (p<5%) was observed, the expected net benefits were positive in all the counties. The overall $V_{(bs)}$ was Ksh 729.97 ± 11.59, n=99 in Siaya. This was Ksh 399.12 ±265.29 (n=73) and 1,309.93 ± 84.69 (n=100) in Kisumu and Homa bay counties respectively. There was a significant difference between the mean $V_{(bs)}$ of those convicted of *fishing using beach seine* and those convicted of *being in possession of beach seine.*

5.3.1 Expected net benefits to fishing crews

The mean v_{bs} to crew was Ksh 746.77 ± 9.79 (n=184) with Ksh 792.79 being most common. A significant difference in v_{bs} to the crews was observed between the three counties. This was highest in Siaya (v_{bs}=734.99 ± 9.35; n=96, mode Ksh 753.80) followed by Kisumu counties (v_{bs}= 486.23 ± 76.06; n=14, mode Ksh 172.57) and Homa Bay county (v_{bs}=811.35 ± 4.45; n=74).

5.3.2 Expected net benefits to seine owners

Overall mean ν_{bs} to owner of seine was Ksh 1,079.42 ± 274.73 (n=88) with most common ν_{bs} being Ksh 2,706.43. Comparison by counties showed significant difference with highest ν_{bs} in Homa bay county (ν_{bs} = 2,728.94 ± 15.52; n=3) with net benefits to most violators being Ksh 2,706.43. This was Ksh 569.41 ± 266.38 (n=3) and Ksh 374.45 ± 328.26 (n=59, mode 371.88) in Siaya and Kisumu counties respectively. Details of penalties, expected benefits, expected cost and net benefits for violators of beach seine ban in L. Victoria Kenya is shown in Appendix 3.

5.4 Sensitivity analysis

5.4.1 Sensitivity of expected net benefits to changes in detection, arrest and prosecution

Violators of beach seine ban showed different sensitivity to changes in detection and conviction probabilities, revenue from fishing and cost of fishing gear as illustrated by Figure 4. The owners of seines were very sensitive to probability of being detected and would cease to expect positive net benefits at p_d of 0.175 and p_{a_o}=0.30 as illustrated in Figure 4 (*a*, *b*). Increasing probability of being proved guilty and or penalysed affected the expected net benefits (Figure 4*d*) but this remained positive even when pg and pp values were 1(Figure 4c, d).
Increasing probability of detecting a crew fishing in violation of this regulation reduced the expected net benefits but does not deter a crew from attempting this violation given that the ν_{bs} will be Ksh 50.15 even if p_d=1 (Figure 4a). The crew are less sensitive to arrest realising zero expected net benefits when p_{a_c} is increased to 0.4960. Being proved guilty and being penalised did not affect the expected net benefits to crews significantly (Figure 4c, d).

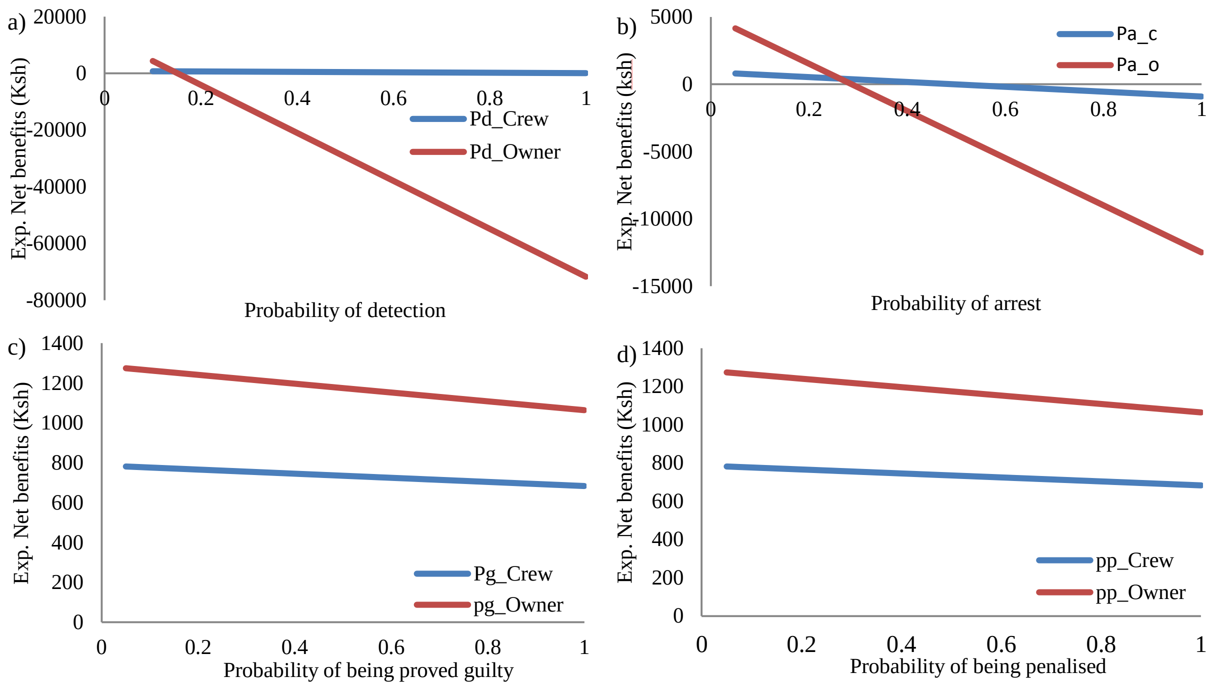
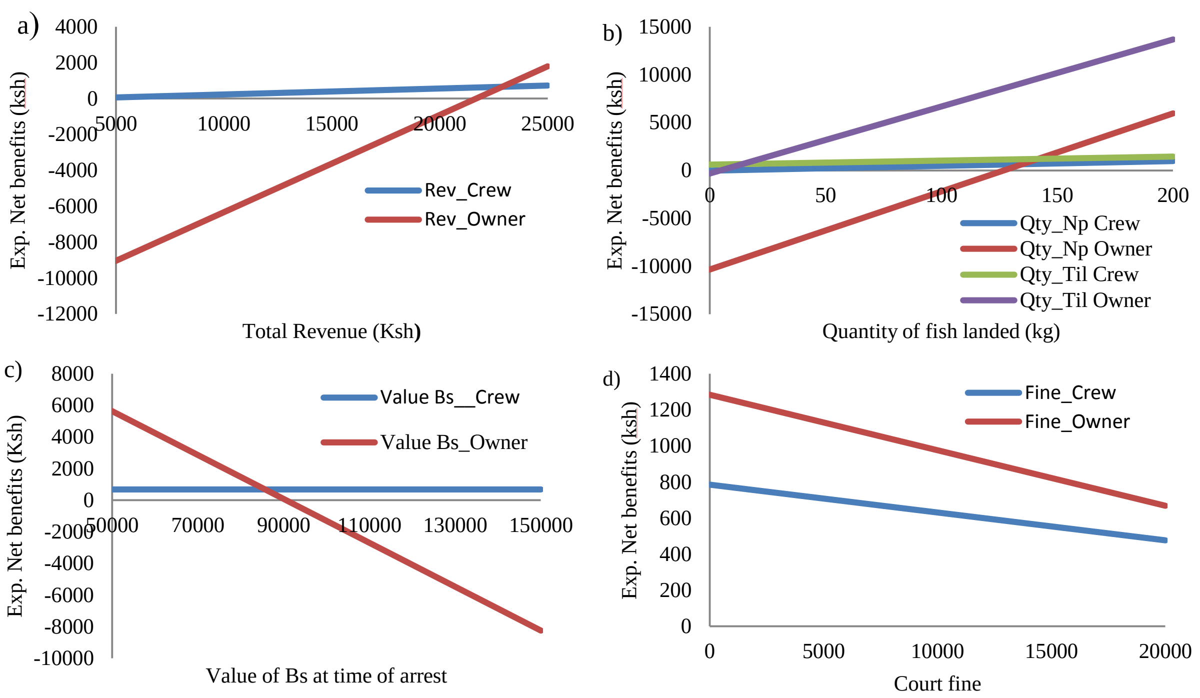


Figure 3: Sensitivity of expected net benefits to changes in enforcement variables –a) detection, b) arrest, c) proven guilty, d) penalty to beach seine ban violators

5.4.2 Sensitivity of expected net benefits to changes in revenue, cost of inputs and fine

Changes in quantity of fish caught, total revenue and cost of inputs affected the net expected benefits to the violators differently with owner of seine being more sensitive to it (Figure 5). The total revenue from a day's operation responded more to changes in quantity of Nile perch as opposed to that of tilapia in catch. Owners of seines make no profits when the value of catch from beach seining violation falls below Ksh 21,685. This violation was beneficial to the crews as long as the total revenue did not go below Ksh 3,100 (Figure 5a). As illustrated in Figure 5b, this model predicts that this violation would not be profiting to the owner of seine if quantity of Nile perch falls below 126 kg. On the other hand, the crew will have positive expected net benefits as long as the quantity of Nile perch in catch does not fall below 3.23 kg.
Beach seine owners will cease to get positive expected net benefits if value of seine at time of seizure exceedes Ksh 90,650 or 60% of its value when new as shown in Figure 5c. Although increase in fine predicted reduced rate of violations, any amount of fine to these violators between Ksh 0 - 20,000 would not stop violation of beach seining ban (Figure 5d).



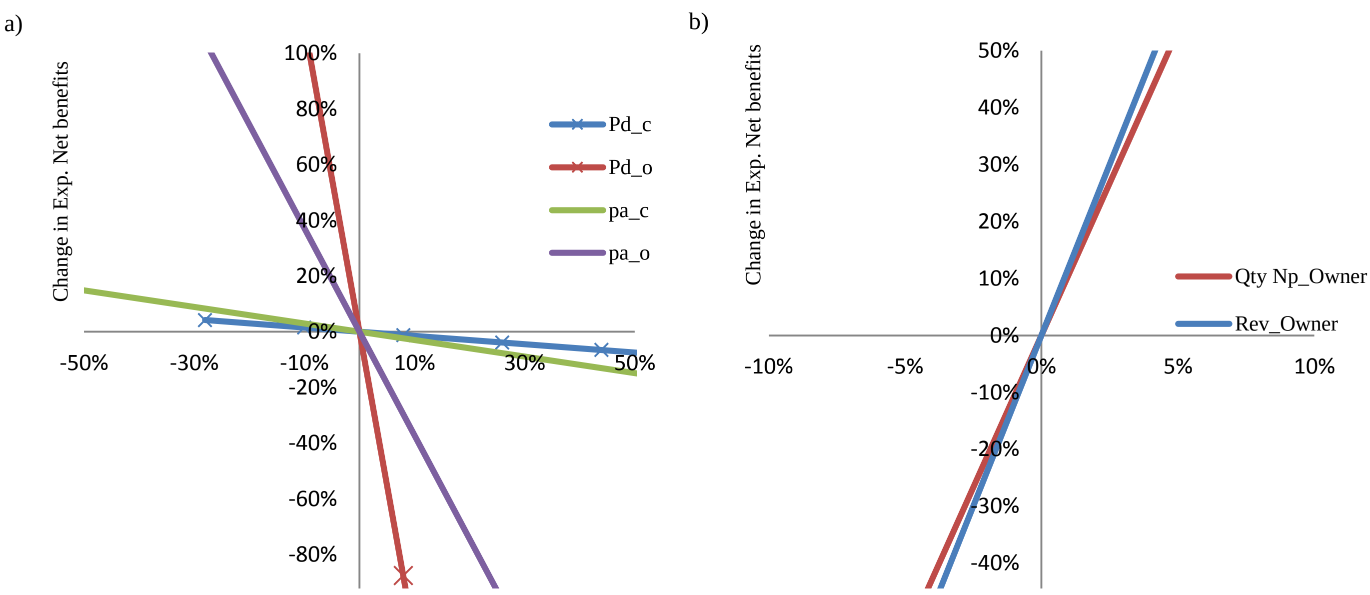


Figure 5. Most responsive variables in enforcing beach seine ban; a) enforcement variables, b) revenue variables

6 DISCUSSION

This study showed that there are benefits associated with violating ban on beach seining and that the benefits are high although accrues to violators only if not arrested. The benefit is expected to vary with a different arrangements between crew and owner of seine, with fishing grounds, seasons and fish prices alongside any form of investments that could lower probability of arrest. However, being an illegal activity, there are uncertainties surrounding the data on catch rates and value of fish caught with Mbuga *et al.* (1998) hinting the possibility of catch from such violations going for considerably lower prices. Overall, the observed expected benefit is important and could be a driver to violating of this ban.

Although the probabilities of a violation being detected and a violator arrested are fundamental elements of enforcement, the observed values were low (p_d=0.139, p_a_c=0.114 and p_a_o=0.226). There was a general increase in detection and arrest of violators from 2007 attaining highest figures (0.3021) during 2009/10 FY. This increase could be attributed to Implementation of Fisheries Management Plan (IFMP) project during which monitoring control and surveillance (MCS) was strengthened and Beach Management Units (BMUs) reformed and legally empowered as co-managers of the fisheries resources. Overall, however, there is a high probability of not being arrested even after being detected, and the probability of not arresting crews during violation is higher (88.64%) than that of the owners of beach seine (77.37%). This difference could be attributed to the fact that most crews abandon the gear once enforcement officers are spotted while on the contrary, some seine owners get tempted to follow their seized gears in an effort to be pardoned thereby raising probability of arresting them. Most enforcement activities are done from small canoes and small pick-up vehicles. This could contribute to not arresting a violator or seizing gear, after detection, once carrying capacity is reached.

The high probability of proving a violation in court (99.0%) and penalizing the violator (98.9%) indicates an effective prosecution and judicial system with regard to this violation. Although penalties to beach seine crews and seine owners were not significantly different, the expected cost was, particularly where the seine owner forfeited the gear as well. The fines to violators did not take cognizance of the concept of marginal deterrent described by Stigler (1970). Many scholars have recognized the role of probability and severity of penalties in making a crime less attractive. Strigler (1970) points at minimizing chances of violations not being detected, maximizing probability of saction after detection, speeding up the process from detection to saction, and making sactions large as basic means of improving compliance. This study however, indicated that although increasing severity of penalties reduced rate of violation, the fines prescribed in the Fisheries Act could not stop this violation even if the upper limit (Ksh 20,000) was applied. This observation concurs with views of a number of experts who argue that severer penalty is not in the first-line of measures in the control illegal fishing (Coelho, *et al*., 2008; Eggert & Lokino, 2008).

There may be violators who invest in informers who relay information of pending enforcement operation, while others used may have used bribery and other forms of corruption along enforcement and judicial processes as earlier described by Mbuga *et al.* (1998). This study assumed these avoidance strategies, though Malik (1990) and Polinsky & Shavell (2001) point out these could impact negatively in control of crime of this nature.

Although this study identifies probability of detecting a violation as most important, the observed value (mean p_d=0.139) imply that there is 86.11% chances that one would violate this regulation without being detected and thus a violator is 86% sure of reaping the benefits (Ksh 786.34 and Ksh 12,811.51 for crew and seine owner respectively). The observed high probability of not being arrested further implies that even among the 14% of violators detected, a violator still has 89% or 77% chances of getting away with the benefits. This scenario appears not only be too attractive but also less competitive among risk averse and or law abiding members of the community and that, the risk takers may only view the ban as a ring-fence around their illegal activity. It is evident that enactment of regulations does not automatically remove the benefits from violation and the need for effective enforcement and judicial mechanisms is paramount. The p_d value where beach seine owners will no longer make positive net benefits (p_d=0.175) translates into an increased surveillance by 25.94%. Moreover, this implies that the seines will be detected within their first year of introduction (its value exceeds 60% of its initial value when new) resulting in negative net expected benefits to seine owner.

Stemming from the probabilities of detection to conviction, expected benefits and costs of violation, it is clear from this study that the expected net benefits of violating beach seining ban in L. Victoria is positive. This is further supports the introduction of new seines and possible replacement of those seized exhibited by the frame survey data. In situations of high unemployment and poverty typical of the communities living around L. Victoria, a positive expected net benefit to violators makes the violation very attractive to both the crews and investors in beach seining. Although empirical evidence supports the role of incentives in criminal behavior, the high positive values indicated by this study do not seem to explain why the majority of fishers act in a way consistent with the law thereby suggesting that other factors could as well be contributing to compliance. Robinson and Darley (1997) indicated that other than the expected pay-offs, people follow the rules to avoid disapproval by one's social group, viewing violations as immoral. Enactment of this regulation was reached in consultation with the fisher community, thus the majority view it as fair and for their own good. This perception seems to have enhanced acceptance of this regulation, a fact in aggrement with justice research (Tyler, 1990; Huo *et al.*,1996). Although the moral and legitimate concerns were not quantified in this study, this observations hinted some form of normative influence concurring with Kuperan and Sutinen (1998) and Sutinen and Kuperan (1999).

Eggert and Lokino (2008) working with artisanal fisheries of L. Victoria in Tanzania indicated the existence of small groups of persistent violators who found constant violation beneficial strategy, irrespective of deterrence variables or legitimacy and social variables. As observed by Eggert and Lokino (2008) and Scullion in FAO (2005), the beach seine ban violators in Kenya seem to perfect the art through unmeasured investments on evasion, bribery and rent seeking.

7 CONCLUSIONS AND RECOMMENDATIONS

This study confirms high profitability of violating beach seining ban in L. Victoria. This arises largely from weak probabilities of detecting the violation and arresting perpetuators although prosecution and conviction of those arrested was effective. The observed high expected benefits to violators and high probabilities of getting away with the benefits seem to make this very attractive to risk takers. Whereas regulations are obviously important in securing long-term benefits of a fishery, effective enforcement of regulations is critical in fisheries management if its objectives are to be realized. Making a criminal act less profitable to a criminal seeking to perform it is obviously a better way of preventing crime as opposed to seeking to make it impossible to commit. This study demonstrates that the expected net benefit to violators was most sensitive to probability of detection and arrest thereby having greatest impact on violation rate. Owners of beach seines are more sensitive to this as opposed to the crews. Being the employers of the crews, targeting seine owners is both effective in addressing the violation rate and also a socially more acceptable strategy. Improving the probabilities and efficacy of detecting owners of beach seine by 26%, with subsequent seizure of the gear within their first year of use is therefore suggested. Consistency in this could further keep check on violators who may make temporary withdrawals. Although prosecution and probability of being penalized was high, the need for ensuring marginal deterrence could be improved on in the legislation and or having fisheries specialists as prosecutors of such cases. Setting up and operationalizing specialized fisheries enforcement unit is further recommended. This goes along with building the capacity both in-terms of skill and equipment alongside logistics that go with effectiveness.

This study further recognizes the positive role of regulations and other social concerns in compliance to regulations alongside the basic model predictions. Continued violations by small groups of perpetuators risks compromising the social and legitimate concerns of those complying, a situation which must be checked. Further, seeking legitimacy and social variables of violating the proposed regulation as well as mechanisms that would decrease the motivation to pursue it should be treated fundamental. Investigations on social variables of this violation as well as evasion investments could further be investigated.

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8 APPENDIX 1

Summary of results of enforcement of ban on beach seining in L. Victoria Kenya (source: MCS national working group report - Kenya)

Financial Year (FY)	**Quarter**	**No. of suspects arrested**	**No of BS seized**	**Enforcement effort** [4]
2004/2005	Q1	74	154	15
	Q2	42	126	18
	Q3	36	73	12
	Q4	16	102	15
2005/2006	Q1	23	56	14
	Q2	27	41	13
	Q3	8	19	9
	Q4	13	29	11
2006/2007	Q1	11	13	7
	Q2	17	28	12
	Q3	11	18	12
	Q4	16	17	8
2007/2008	Q1	6	29	10
	Q2	10	17	12
	Q3	6	13	9
	Q4	11	17	9
2008/2009	Q1	10	8	8
	Q2	8	17	8
	Q3	6	11	8
	Q4	17	14	6
2009/2010	Q1	6	16	11
	Q2	0	8	10
	Q3	8	6	10
	Q4	3	9	6
	Totals	385	841	253

[4] Enforcement effort interms of number of days enforcement unit is out for operation.

9 APPENDIX 2

Summary of penalty, Expected benefit, Expected cost and Expected net benefits of violating beach seining ban in L. Victoria Kenya between 2001 and 2012.

Variable		Siaya		Kisumu		Homa bay		Overall	
		Owners	Crews	Owners	Crews	Owners	Crews	Owners	Crews
Penalty	Mean	3,583.33	4,049.48	6,520.34	11,428.57	8,750.08	9,047.30	7079.00	6620.92
	Std error	2,113.12	422.97	626.35	626.47	861.66	531.86	508.49	370.62
	Mode	N/A	3000	5000	10,000	10,000	10,000	10000.00	3000.00
	Sample size	3	96	59	14	26	74	88	184
Expected Benefits	Mean	12,223.57	776.13	12,135.62	700.51	14,413.08	815.83	12,811.50	786.34
	Std error	270.47	6.68	317.05	34.41	3.64E-13	1.33e-13	239.49	4.87
	Mode	12,419.51	788.54	14,413.08	558.55	14,413.08	815.83	14,413.08	815.83
	Sample size	6	96	59	14	26	74	91	184
Expected Cost	Mean	11,654.16	45.60	11,757.18	229.55	11,684.13	75.75	11,732.08	71.72
	Std error	70.15	4.60	25.54	37.83	15.52	4.45	18.19	5.38
	Mode	N/A	34.74	11,706.64	385.98	11,706.64	83.73	11,706.64	83.73
	Sample size	3	96	59	14	26	74	88	184
Expected Net Benefit	Mean	569.41	734.99	378.45	486.23	2,728.94	811.35	1,079.42	746.77
	Std error	266.38	9.35	328.26	76.06	15.52	4.45	247.73	9.79
	Mode	N/A	753.80	2,706.43	172.57	2,706.43	803.37	2,706.43	803.38
	Sample size	3	96	59	14	26	74	88	184