CHAPTER THREE

RELEVANT LITERATURE ON MEASURING NONCOMPLIANCE WITH FISHERY REGULATIONS

3.1 Introduction

Future viability and benefits from fisheries have been negatively affected by the practicing of illegal fishing and noncompliance with fishery regulations. This has become a global problem, presenting serious threats to fish stock rebuilding (MEA, 2005; Sumaila *et al*. 2006). Serious decline in inland water stocks has been reported in developing countries; the number of un-harvested inland fish stocks has been steadily decreasing; from 40 % in 1990 to 23 % in 2004. Despite the existence of fisheries management policies, fisheries in developing countries are encountering a serious threat of over-fishing (Allan *et al*. 2005). Many factors are believed to contribute to this problem; among them are difficulties in enforcing regulations and inefficient institutions to handle the problem.

The lack of effective enforcement and monitoring mechanisms also encourages corruption and creates a good environment for illegal fishing (Eggert and Lokina, 2010). Thus, fisheries' sustainability has been far more difficult to achieve in developing countries although many efforts have been made to rebuild fish stocks. For instance, official limits on the size of fishing nets and harvests, as well as other management measures, have been used to help stock recovery and reduce over-fishing and consequently illegal fishing (FAO, 2003). It is also believed that Africa's fisheries crisis and steady decreases in fish stocks are attributed to the use of destructive gear and the practice of illegal fishing (MEA, 2005).

Despite its major role in the failure of fishery management, illegal fishing has received little attention in the past (Anderson, 1989, Sutinen and Hennessey 1986), particularly in the field of fishery economics and policy making studies (Charles *et al*. 1999). However, illegal fishing behaviour has gained considerable attention recently in both fields because of the increasing recognition of the damage and loss associated with this problem (Sumaila *et al*. 2006). Many studies have argued that fishery regulation failure is attributed to costly and weak enforcement and monitoring of compliance with laws and regulations, in addition to tolerance to corruption and cheating (Charles *et al*. 1999 and MEA, 2005).

Many theoretical and empirical studies have been conducted to analyse reasons for noncompliance with fishery regulations by adapting different static, dynamic and policy oriented approaches. Different types of noncompliance with fishery regulations are cited in the literature such as: fishing in closed areas, catching with non-prescribed mesh size or fishing in a prohibited zone or any behaviour against the law (Akpalu, 2008a; Charles *et al*., 1999; Srinivasa, 2005; Furlong, 1991; Hatcher *et al*. 2000 and Sumaila *et al*. 2006). However, noncompliance with mesh size regulations is found to be the most common and biggest problem in Africa (Atta-mills *et al*, 2004; Akpalu, 2008a, 2008b; 2009; Eggert and Lokina, 2010).

This chapter provides a study of the relevant literature on noncompliance with fishery regulations. The next section reviews the approaches for analysis of determinants of noncompliance with fishery regulations under static and dynamic formulations. Empirical approaches used to analyse factors influencing violation rate are reviewed in section three and the chapter concludes with a summary.

3.2 Approaches and methods used in compliance analysis

Noncompliance with fishery regulations has important implications for the welfare of fishing communities. The framework schema of Figure 3.1 is adapted from Sutinen and Kuperan (1999) and extended to include determinants of noncompliance with fishery regulations in dynamic approaches. The following sections present a review of the various components of the compliance modelling framework presented in Figure 3.1.

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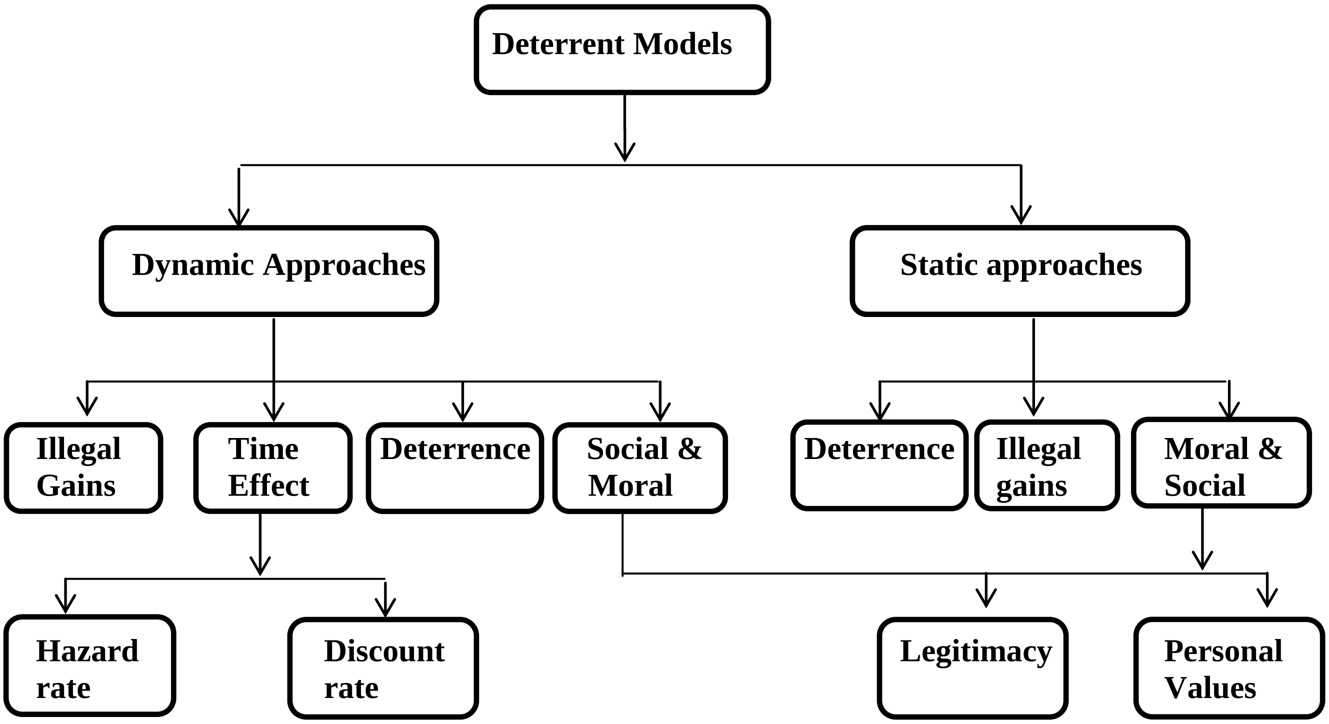

Figure 3.1: Approaches and factors considered in analyses of determinants of noncompliance with fishery regulations
Source: Modified/extended from Sutinen and Kuperan (1999)

3.2.1 Static approach to study noncompliance with fishery regulations

Becker (1968) was the first to study the behaviour of law breakers. He developed the first theoretical deterrence model to analyse the choice between legal and illegal options for a criminal to maximise his/her utility from illegal activities. Static deterrence models assume that a violator faces a single time period decision problem of maximising expected utility from illegal fishing, i.e. the choice of either to follow fishery regulations or not. The model's implicit assumption is that a fisher has a fixed amount of time to be allocated to both legal and illegal fishing. The gain from violation is not guaranteed because of the probability of enforcement leading to detection and consequent punishment. This motivated the use of expected utility in deterrence models.

In the static context, the main determinants of the choice of an illegal option are the profit that an offender gains from the illegal practice and the low probability of detection combined with a small fine (punishment). Many studies have followed Becker's model of the economics of crime and punishment under static formulations (Charles *et al.* 1999; Furlong, 1991; Hatcher and Gordon, 2005; Kuperan and Sutinen, 1998; Sutinen and Kuperan, 1999; Sumaila *et al.* 2006).

The high profit that fishers gain by violating national laws is the main incentive for noncompliance (Charles *et al*. 1999; Hatcher and Gordon, 2005; King and Sutinen, 2010 and Sumaila *et al*. 2006). Sumaila *et al*. (2006) estimate gains from illegal fishing by a set of apprehended illegal fishing vessels to amount to about 24 times the fine paid as a punishment. King and Sutinen (2010) estimate it to be 5 times the penalty paid.

One major extension of the static model is the attempt by Charles *et al.* (1999) and subsequently Sumaila *et al.* (2006) to consider effects of avoidance activities. Charles *et al*. (1999) applied a micro-economic static model to determine the level of enforcement a policy maker should allocate in the presence of evasion activities for optimal management of a fishery. The study showed that fishers react to enforcement by focusing more on avoidance behaviour than reducing violation rates. This means that improvement of law enforcement in fisheries needs to be grounded in a good understanding of avoidance behaviour.

The recommendation from the pure deterrence model is that detection should be increased and that penalties should be high to offset gains from violation. On the other hand, Furlong (1991) conducted a self-reported survey among Canadian fishers and found that fishers are more sensitive to increases in likelihood of detection than increases in penalties. Some studies have argued that the policies suggested by the purely traditional deterrence model cannot be applied to real life and also do not give a complete explanation of compliant behaviour. Kuperan and Sutinen (1998) pointed out that profit from and cost of illegal behaviour, are not enough to describe fishers' decisions.

Based on this last argument, some studies have extended the traditional deterrence model to account for moral, social and legitimate dimensions, known as normative factors that are believed to be important in determining violation among fishers (Akpalu, 2008a/2008b; Eggert and Lokina, 2010; Hatcher *et al.*, 2000; and Kuperan and Sutinen, 1998). These factors measure a fisher's behaviour and beliefs towards his peer violators and how these influence his values. It also measures a fisher's perception of the violation itself and his perception of regulations as effective or fair.

The influences of social and moral factors have been accounted for in theoretical and empirical applications to examine their impact on compliance. Results of empirical investigations revealed that such factors can have either positive or negative influences. Positive influence implies supporting or encouraging compliance and considering violation of regulations to be bad behaviour. On the other hand, negative influence result from the perception that violation is not wrong, which is an attitude making noncompliance dominant and a normal part of their regular job. However, the normative effect was found to be smaller in comparison to the deterrence effect in a study by Hatcher and Gordon (2005).

One of the shortcomings of the static model is the assumption that two different agents have an equal set of constraints and the only factor that differentiates them is their affinity for taking risks. This distinction was argued to be immeasurable by Davis (1988), which makes the static model limited. The static model also does not account for the effect of discounting future benefits, i.e. discount rates (Davis, 1988). Static models by nature cannot measure the optimal rate of violation over time.

3.2.2 Dynamic compliance modelling approaches

Dynamic models have been developed to consider allocation of resources over time (i.e. to study inter-temporal allocation decisions). In dynamic formulations, the fisher will be optimising his gains over time until he gets caught, because the crime is committed repeatedly. The two periods dynamic deterrence model (DDM), as developed by Davis (1988), postulates that violators seek to maximise expected discounted profit over both periods. In the first period, offenders gain from illegal activities until the time they get caught and pay a fine. Violators will then comply and engage only in legal activities thereafter, concluding the model' second period.

Justifications for using a dynamic model for illegal fishing analysis are motivated by many legitimate considerations, most important of which are the repeated nature of the crime (i.e.

violation occurs repeatedly), the change in the danger of getting caught over time (detection time evolves), and differences on fishers extraction rate of the resource. These factors imply a temporal objective of not analysing single period gains but rather maximising the sum of the stream of net benefits over time (at least over two periods). It also motivates inclusion of evasion efforts with the aim of prolonging the time before getting caught.

The difference in skippers' time preference is also a very important factor in deterrence analysis since it gives information about their patience (choice between consumption now or in the future). A study by Akpalu (2008a) found that impatient fishers have higher violation rates. It also provides information on skippers' poverty levels, given the fact that that poorer fishers are found to have higher discount rates.

Conclusions from the current dynamic model with constant probability of detection reveal that noncompliance is more likely to be deterred by increasing the probability of being caught than by raising the fine (Akpalu, 2008a; Davis, 1988). The DDM adds the effect of the discount rate and modifies probability of detection from being subjective in the static model to a conditional probability that explains the fact that the profit from violation is conditional on the violator's survival.

Although the standard DDM represents the most advanced analytical framework widely used for analysis of compliance with fishery regulation, it suffers from some deficiencies. For instance, violation rates in the DDM have so far been mainly specified only as "intensity of violation" (Akpalu, 2008a), whereas "frequency of violation" has been used only in static deterrence models (Eggert and Lokina, 2010; Furlong, 1991 and Sutinen and Kuperan, 1999). No study has yet used frequency as a measure of violation rate in a dynamic formulation, in spite of the proven advantages of using frequency in static deterrence models. This is an important gap in the existing theoretical and empirical literature.

First, intensity of violation, which is measured by the value of juvenile fish in an illegal catch per day averaged over the past week's catch, may fit developed countries but is highly unlikely to work well in developing countries where property rights are less well defined and it is relatively easier for fishers to escape being caught. This makes it very hard to estimate the total catch per day that includes violating harvests, and hence presents a data problem. Second, by not employing frequency as a measure of violation rate, one misses the opportunity of capturing the direct link between violation rates and opportune time periods for illegal fishing (seasonality). This is due to the fact that, during months of active breeding the quantities of small fish are high, which encourages illegal fishing compared to months of no breeding. Thirdly, the use of frequency also helps to classify fishers into categories of violators, a typology that will help policy makers and managers design policy measures and instruments suited for each group. Finally illegal catches are not sold on formal fishing markets, but are rather concealed and sold out of monitors' notice, outside formal channels. Therefore this study intends to extend the current DDM by introducing frequency of violation and hence identify typologies of violators.

Standard DDM formulations have also been limited to the case of probability of detection that doesn't depend on time assumptions. The present study intends to fill these gaps by extending the current DDM to relax these assumptions and derive analytical results under alternative specifications allowing for probability of detection that depends on time and measuring the rate of violation by distinguishing different typologies of violators according to their violation rates measured by frequency of noncompliance.

3.2.3 Empirical studies based on static and dynamic approaches

To design more effective deterrence mechanisms, more research is needed to gain better understanding of fishers' noncompliant behaviour. Illegal fishing is difficult to observe, however, and information about it cannot be obtained from government and fisheries departments' statistics but is mostly based on surveys and interviews (King and Sutinen 2010). Generally, there is little published research on empirical regulatory compliance. Some empirical studies of noncompliance with fishery regulations have been conducted in many parts of the world, generating results that differ across countries. Some studies analysed the extent of violation by looking at how frequently fishers violate (Sutinen and Kuperan 1999; Furlong 1991; Eggert and Lokina 2010; King and Sutinen 2010) and hence provide information on violators' degrees of violation.

Frequency of violation has been measured in different ways in studies conducted in different countries. A study of fishers in Lake Victoria measured violation of minimum mesh size regulations by the number of months when such illegal fishing was practiced within the year (Eggert and Lokina 2010). Furlong (1991) used proportion of violation (proportion of regulatory regimes violated) in a typical fishing trip in a specific season as a measure of frequency of violation. Hatcher and Gordon (2005) measured violation rate as the percentage of landings over quota in the previous year, whereas Kuperan and Sutinen (1998) measured violation rate by the number of days a fisher has fished in a prohibited zone.

In analysing factors affecting compliance with output restrictions (quotas) among fishermen in the United Kingdom, Hatcher *et al. (*2000) measured violation rate by a fisher's decision to violate or comply. On the other hand, in a dynamic formulation Akpalu (2008a) measured the rate of violation of fishers in Ghana by looking at the intensity of violation, calculated as the value of juvenile fish in an illegal catch per day averaged over the past week's catch.

Different econometric models have been employed to suit the different ways in which violation rates are measured. Eggert and Lokina (2010) and Hatcher and Gordon (2005) used ordered Probit models to analyse determinants of violation of fishery regulation because of the ordered nature of the latent dependent variable. In both above cited studies, the ordered likelihood function was used to predict changes in the probability of violation in response to changes in considered determining factors. Eggert and Lokina (2010) further measured the extent of violation within one fishers' typology (occasional violators) by truncating the data to exclude both non-violators and chronic violators.

Hatcher *et al.* (2000), Kuperan and Sutinen (1998) and Akpalu (2008a) all investigated fishers' decision on whether to violate or comply using binary Probit models. Kuperan and Sutinen (1998) and Akpalu (2008a) subsequently used the Tobit model because their dependant variables were censored at zero. Furlong (1991) also used Tobit models to estimate the violation supply function. The Tobit models are used to avoid the problem caused by censored data if the dependent variable is continuous but sensored at zero, as some fishers do not violate for reasons other than their moral standing, like high cost of illegal nets (Long, 1996).

Studies that classify violators according to their violation rate believe that classification will help managers understand each group and hence formulate policy accordingly. Generally, non-violators are found to be significant in numbers in many countries, which supports the positive influence of normative factors (Eggert and Lokina 2010; Furlong, 1991; Kuperan and Sutinen, 1998; Sutinen and Kuperan 1999; King and Sutinen, 2010).

The typology of violators also differs across countries. For example, Eggert and Lokina (2010) found that about half of the surveyed fishers in Tanzania were violators. On the other hand, Furlong's (1991) surveys reported that about two thirds of fishers violate while Kuperan and Sutinen (1998) reported 75 % violation rates among fishers in Malaysia. In Ghana, however, violation (the use of light attraction equipment) was found to be 46.9 % (Akpalu, 2011).

Other studies suggested that some personal characteristics are important in compliance analysis. Furlong (1991) for example, conducted a survey of Canadian fishers and included age, and income from fishing and other employment as variables. In his estimation, although these variables had the expected sign, age was the only variable with statistical significance. On the other hand, Sutinen and Gauvin (1989) found, in their estimation of compliance in the lobster fishery of Massachusetts, that the effect of all three (i.e. age, experience and fishing as source of income) on noncompliance to be statistically significant.

There has been a lot of debate in literature about the probability of detection and the way it enters the model and how to measure it. Probabilities of detection are either estimated separately or jointly in an econometric model. The leading work by Kuperan and Sutinen (1998) explains this very well. They considered probability of detection to be a salient issue of compliance and hence better understanding of how this variable behaves is very important. Probability of detection itself is the joint estimation of probabilities, which include probability of detection, the probability of an arrest given detection, the probability of being taken to court given arrest, and the probability of being found guilty given that the fisherman is taken to court (Akpalu, 2008; Eggert and Lokina, 2010; Furlong, 1991; Kuperan and Sutinen, 1998; Hatcher *et al.*, 2000; Sutinen and Kuperan, 1999).

This implies that probability of detection by itself is a function of a number of factors. Kuperan and Sutinen (1998) suggested measuring the overall probability of detection variable in three different ways. They firstly proposed an exogenously determined probability of detection, which makes the overall probability of detection not included in the main violation model directly. Instead, exogenous determinants such as enforcement and avoidance activity enter the deterrence model. This method is adapted by this study for the development of the modified DDM which will be explained in details in chapter five.

The second way is to jointly estimate probability of detection as part of the violation model. For example, the overall probability of detection is treated as an explanatory variable and used in the main deterrence function. In a study by Furlong (1991), the probability of detection was jointly determined in the model and divided into four stages, probability of detection, prosecution, conviction and punishment in the function. The said study encountered both problems of co-linearity and simultaneity due to the joint estimation of the overall probability of detection and violation function.

The third method entails an estimation of the probability of detection by one variable measuring the number of times the violator has been seen by the police landing an illegal catch or using unauthorised gear or by the perceptions of fishers about the chances of detection as increasing or decreasing. Our study chooses this method, which helps overcome the endogenity problem. In a study by Hatcher and Gordon (2005), the probability of detection is measured by including the subjective probabilities as a regressor in the violation function.

Almost all these studies (except Hatcher and Gordon, 2005) faced the problem of endogenity due to reasons explained in the preceding paragraphs (Akpalu, 2008a; Eggert and Lokina, 2010; Furlong, 1991; Hatcher *et al.*, 2000; Kuperan and Sutinen, 1998; Sutinen and Gauvin, 1989). Hatcher and Gordon (2005) argued that the reason for not having endogenity is due to the fact that the violation rate and probabilities of detections were not estimated in the same time period (fishers were asked about their previous year's violations). This is based on the assumption that the perceived risk has not changed significantly within the time under consideration. Hence, the simultaneity problem falls away. In some studies, instrumental variables have been used (Akpalu, 2008a) to solve this problem, but Hatcher *et al*. (2000) used a two-stage simultaneous equation system.

Kuperan and Sutinen (1998) argued that there is an inconsistency in the performance of variables measuring the probability of detection. This inconsistency stems from the fact that the probabilities are subjective and are difficult to analyse because of the lack of knowledge about the factors affecting their generation. Furthermore, the respondents may not understand the concept of probabilities.

Another problem related to compliance analysis is the strong correlation between variables measuring normative factors. The close link and interdependency between social, moral and legitimate factors usually create this type of problem (Akpalu, 2008a/2008b; Hatcher *et al*., 2000; Hatcher and Gordon, 2005).

Some factors in the empirical model cannot be measured directly and hence proxies are used. For instance, probability of detection is measured by asking respondents about their perception of probability of detection, ranking on a five-point scale ranging from very high to very low (Hatcher *et al*. 2000). Akpalu (2008a) for example, measured the discount rate using experimental choice design. The skippers were asked to choose between two hypothetical fishery projects: Project A, which was supposed to increase skipper's income once by an amount at the end of the month in which the data were collected, and Project B, which increased it once by twice the amount in six months' time. After the choice was made, the respondent was asked to indicate the value for Project B that would make him indifferent between the two projects. Depending on the fisher's choice, the discount rate is calculated as the amount quoted by the skipper over the amount that the project offers.

Enforcement is measured by asking fishers whether they perceive the current enforcement to be adequate and fair (Sutinen and Kuperan, 1999). The moral variables refer to the fisher's beliefs about violation given the fact that some people are impressionable and act according to others' standards (Tyran and Feld 2002). Moral variables are also measured by the fisher's moral standing in the community, that is, when fishers are keen about their moral standing in the fishing community and how it might psychologically impact on them (Sumaila *et al*. 2006). Moral aspects such as acceptance of bribes by police when violators are arrested have been found to be very significant in Tanzanian fisheries, where corruption and poverty make it difficult for fishers to comply with regulations (Eggert and Lokina, 2010).

The different measurement of the social and moral factors as explain above makes the effect of normative factors differ or may have both negative and positive effects on compliance with fishery regulations**.** The measure of the normative factors that one should choose in the model depends on the current fisheries environment in terms of the social relations within the fishing community under study and how fishers value violation and the way regulations are enforced, considering their fairness and effectiveness.

Empirical results from compliance studies are different. Some papers found that to deter violation, deterrent variables are the most important factors (Hatcher and Gordon 2005), while others found both deterrence and non-monetary variables such as social and moral standards to be equally important (Akpalu, 2008; Hatcher *et al*. 2000, Eggert and Lokina 2010; Kuperan and Sutinen 1998). For instance, Eggert and Lokina (2010) tested for exclusion of either the deterrence or normative factors from the model and the results showed that both deterrence and normative factors are very important in explaining violation behaviour.

It may also happen that the regulation officer could be socially excluded from the community in his or her efforts to enforce the regulations. This creates an incentive for a regulator to accept bribes in order to continue keeping social ties with his community and avoid shame-based sanction (Akpalu *et al*, 2009).

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Empirical studies generally suffer from data accuracy and difficulties in obtaining quality and reliable information. This may refer to misreporting, not understanding concepts and giving misleading answers since reporting own violation is not an easy task. The concepts of probabilities and perceptions are new to fishers, who are most likely to have only primary education. In addition, some variables in compliance analysis cannot be measured directly; hence proxies are used, which may also have some effect on model parameters' estimates.

There is a strong view in the empirical literature that for compliance to be applied in a proper way, a good management system should be designed and put into effect since the management regime has a direct influence on compliance (Hardin, 1968). A quite divergent view on which management system is most effective for better compliance with regulations exists in literature, however. For instance, many authors agree that the most suitable management system to ensure compliance is a properly implemented co-management system (Ostram, 1990; Eggert and Ellegård**,** 2003; Jentoft, 2000; Nilsen, 2003, Hanna, 2003; Nielsen and Mathiesen, 2003). Jentoft (2000) attributed perfect compliance under this regime to the improvement of the legitimacy of fisheries management system such as sharing decisions, creating a feeling of fairness and justice and greater understanding of regulations. He further indicated, though, that if co-management is not handled carefully it may lead to loss of legitimacy. Nilsen (2003) ascribed the success of compliance to the fact that managers and decision makers lack knowledge about the factors that affect compliance and legitimacy within the fishers' communities. Legitimacy is defined as the perception of the fishers about regulations. He concluded that if there are large numbers of fishers involved in regulation formulation, legitimacy is more easily achieved.

Hatcher *et al*. (2000), on the other hand, argued that co-management as a fishery management system is unlikely to result in high levels of compliance as long as output controls are concerned. They pointed out that it is not co-management *per se* but the flexibility in the management system that brings about efficient fishery management in many regulatory regimes. The management approaches that are currently applied in most developing countries are based on centralised government intervention and have proven inadequate to deal with the issue of compliance with fisheries regulations.

3. 3 Summary

This chapter reviews the literature on measuring noncompliance with fishery regulations and its determinants. Several deterrence models have been developed to study noncompliance with fishery regulations in static and dynamic decision frameworks. The static approach assumes violators maximise expected utility from fishing illegally and the gain from violation is not guaranteed because violators might get caught. This model was developed by Becker (1968) and was widely used and one main conclusion from this approach is that higher fine rather than probability of detection is more effective deterrent.

On the other hand, Davis (1988) argues that by taking certain factors into account, like discounting of future profits and the perceived risk of detection, which change over time, deterrence analysis is more realistically modelled as a dynamic decision process. This implied changing the expected gain from "not guaranteed" in the static model to "conditional upon fisher's survival" in the DDM. The DDM has also been applied to noncompliance in fishery deriving results that suggest violation of regulations is more likely to be deterred by increased probability of detection than by increases in fines. Very few studies apply this model, which emphasizes the importance of including discounting in measuring violation, as it has direct effect on policy formulation regarding current and future distribution of resources.

Different econometric models have been specified to conduct empirical deterrence analysis on determinants and extent of the decision to violate. Binary models, ordered choice models and Tobit models are among those used in the empirical literature. Determinants of noncompliance include purely deterrence factors and normative factors. Some econometric problems, such as multi-collinearity among factors that measure normative effects and biased data on self-reporting of violation, are common in empirical estimations of noncompliance with regulations. Co-management has been found to be the most successful regime for compliance with regulations as widely mentioned in the literature.

Existing literature using DDM, is found limited to the case of constant probability of detection and intensity of violation as a measure of violation rate. This study attempts to relax these assumptions by extending and modifying the standard model aiming for a more flexible model as explained in following chapter. First the study will adapt the standard DDM using frequency instead of intensity of violation rates, which allows analysis of factors that determine compliance by typology of violators. Second, the study will adapt the DDM to allow for probability of

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detection that depends on time. The adapted models will then be empirically estimated using data from a survey of fishers in the JAR of Sudan.

CHAPTER FOUR

DYNAMIC DETERRENCE OF NONCOMPLIANCE WITH FISHERY REGULATIONS: THE ADAPTED ANALYTICAL FRAMEWORK AND RESULTS WITH FREQUENCY AS THE MEASURE OF VIOLATION

4.1 Introduction

As discussed earlier in the literature study of chapter three the DDM is commonly used for analysis of non-compliance with fishery regulations. This study adapted the DDM to deal with some of the existing gaps in the application of the model to situations representing artisanal fishery circumstances in developing countries. The DDM adapted for the use of frequency rather than intensity of violation as the measure of noncompliance is presented in the following section. Section three employs the extended DDM to perform comparative static on the sensitivity of optimal violation to a number of key factors of high relevance to compliance with regulations. Analytical results obtained from this modified DDM are then compared with findings of earlier empirical studies employing alternative static and dynamic formulations. The chapter concludes with a summary in section four.

4.2 Dynamic deterrence with frequency measures of violation rate

In the literature, noncompliance is measured by either intensity or frequency of violation. Some empirical studies used frequency of violation to measure violation rate in static deterrence models (Eggert and Lokina, 2010; Hatcher and Gordon, 2005; Sutinen and Kuperan, 1999). Furlong (1991) and Sutinen and Kuperan (1999) assumed that a fisher has a fixed amount of time, part of which he spends fishing illegally but did not explicitly classify violators by type. On the other hand, Eggert and Lokina (2010) adopted a typology of violators but did not account for the dynamic nature of violation, i.e. alternate periods of violation and non-violation for the same fisher, continued repeatedly over time. The said studies revealed that using frequency measures has the advantage of enabling classification of violators by type which is of significant value for effective policy design and targeting.

Fishing in African lakes and rivers is characterised by its seasonal nature. For instance, three seasons of fishing are observed, the abundant catch season, when fishers are able to use their normal techniques of catching fish; scarcity season, when it is hard to obtain a catch by authorised means; and the flood season, when fishing is hard to practice. Fishers cope with this seasonality by changing techniques to suit different seasons' circumstances, which in most cases involve violation. It is therefore important to consider fishing seasonality in analysing compliance with regulation. Eggert and Lokina (2010) explained it implicitly by measuring the rate of violation among artisanal fishers in Tanzania by how frequently fishers violate regulations in terms of months.

Three types of fishermen have been observed in developing countries (Eggert and Lokina, 2010; Kuperan and Sutinen, 1998). The first is the non-violators' group, who always follow regulations (e.g. use prescribed nets) and tend to be mostly well-off fishermen who have alternative sources of income for survival. For this group, using small-sized nets is usually time consuming and the small fish caught with these nets command low prices. The second group can be described as chronic violators, who only own illegal nets because they cannot afford to buy both types of nets. For this relatively poor group, the small-sized fish, though not commercially profitable, guarantees a subsistence catch necessary for survival, especially during seasons of low stocks of large size fish. The opportunity cost of labour of the relatively poor fishers "chronic violator" is almost zero. Their higher dependency on fishing, increases violation and hence make them significantly contributes to the sock decline in JAR.The third group consists of alternate violators who own both types of net using the prescribed nets during fish abundance seasons and illegal sized nets during seasons of scarcity. In addition to enabling use of fishers' typology, frequency measures are less problematic with data. This is because illegal catches are not sold in formal markets as most of the time fishers hide them to avoid being caught and that makes it very hard to find data necessary for deriving intensity measures (e.g. share of illegal catches in total harvest per day).

Despite its revealed usefulness for policy design frequency of noncompliance has not been used yet as a measure of violation rate in dynamic formulations and only intensity has so far been used with DDMs. This study adapted the two periods DDM (Davis, 1988; Leung, 1991; Akpalu, 2008), which postulates that violators seek to maximise their expected discounted profit over two periods. In the first period, offenders gain from illegal activities until the time they get caught and pay a fine. Violators will then engage only in legal activities thereafter, concluding the second period choice problem (as explained in chapter three). In this study the DDM is adapted for use of frequency as the measure of violation rate.

In the following frequency of violation is defined in terms of the number of months during the year a fisher uses under-sized nets. According to that, three groups of violators are defined as follows. Non-violators (NV) referring to those who never violate; occasional violators (OV) are those who alternate between not violating and violating at least once (e.g. one month per year). The last group is the chronic violators (CV) who violate all the time. Eggert and Lokina (2010)
In order to measure frequency of violation, the two periods DDM is specified to suit the middle group (OV). Due to the seasonality of the catch, fishers alternate between fishing legally and illegally in the first period (they own two types of nets). When they get caught, the illegal nets will be seized and fishers will continue using legal nets thereafter. Kuperan and Sutinen (1998) noted that most fishers in developing countries are alternate violators.

NV only use a legal net throughout the two seasons while CV use an illegal net in both periods until they are caught. On the other hand OV might refrain from fishing for a certain time until they manage to buy another illegal net because it is costly to comply with regulations. That causes those who own two nets to alternate between illegal –legal nets in the first period and only legal nets in the second period.

We assume that m is the frequency of illegal fishing measured by the number of sub-periods of fishing per unit time considered (i.e. it could be number of months/days or years of illegal fishing). If in any period the fisher uses a small (illegal) mesh size, he targets both mature and immature fish (i.e. m> 0) and his profit $\pi(m)$ from violation is:

$$\pi\left(m, c, p_a, Q_{m,} E_{m,} s, x\right) = m(p_a Q_m\,(E_{m,} s) - c(E_m)) = m\left(p_a Q_m - c(E_m)\right) \tag{4.1}$$

Where m is the frequency of illegal fishing before detection, $p_{a,}$ refers to the average price of fish caught (mature and immature)[4], Q_m is quantity of the mixed catch of mature and immature fish using illegal net per period of violation, and (c) measures total cost of fishing illegally per period, including a fixed (e.g. sunk cost of the illegal net) and variable (e.g. effort) cost components. The cost variable *(c)* might also include corruption cost (paying a bribe) as an attempt of not being caught, if detected. E_m, refers to the effort used to catch this quantity per unit period of illegal fishing time, and *s* is the stock of mixed catch (mature and immature).

It is assumed that the time of the entire planning horizon is T, which extends to infinity and *(t)* is measured by years; within each year there are months of violation (m) and months of compliance (n). After being caught at the end of the first period and the illegal net is being seized, the fisher will be left with only one option which is to continue to maximise his profit[5] from only legal catches thereafter. The fisher's second period profit $\pi(n)$ is therefore:

$$\pi(n, b, p_n, Q_n, E_n, x) = n(p_n Q_n (E_{n,} x) - b(E_n)) \quad (4.2)$$

Where *(n)* measures the frequency of legal fishing, p_n is the price of normal catch, $Q_{n,}$ is the quantity of normal catch and *(b)* is the total cost (including fixed and variable components) per period of no violation (time of normal fishing). E_n is the effort per time period of legal fishing and *(x)* is the stock of mature fish. Then the sum of the two profits gives the total profit of the violator over the two-time periods planning horizon as:

$$\pi(m) + \pi(m) = m\left(p_{a.} Q_m - c(E_m)\right) + n(p_n Q_n (E_{n,} x) - b(E_n)) \quad (4.3)$$

[4] Average price is used because of the fact that the catch from illegal net include both catches mature and immature and fishers usually sell their catch of mixed sizes to middlemen in weight units (kg).

[5] Though DDM assumes fishers violate in order to maximise profits, in developing countries where rivers and lakes are over-fished, fishers violate for survival and to sustain life (Sterner, 2003).

Given that the assumption of the DDM holds, the violator lacks knowledge about the exact time of detection. However, he has some information about the distribution of the time of detection (Davis, 1988). Thus, we assume a continuous distribution of time of detection (t) with the probability density function (pdf) given by $g(t)$ and the cumulative density function (cdf) given by $G(t)$ so that $g(t) = dG(t)/dt$. Then, the probability of being caught at time (t) is $G(t)$ and the probability of not being caught at time t is $1 - G(t)$.

It is also assumed that if the fisher is caught, he pays a fine F, which is a fixed amount of money plus the cost of the seized illegal catch. According to Davis (1988), the probability of paying the fine is R[6] and the expected present value of the fine is:

$$R \int_0^{\infty} F g(t) e^{-\delta t} \, dt \tag{4.4}$$

The following value function (equation 4.5) states that the fisherman is maximising his expected discounted profit v (.) over an infinite time horizon (the two periods) and the fisher is alternate violator who uses both nets in the first period and when caught , the illegal net will be sized then he will continue fishing legally in the second period. The value function of the fisher is therefore,

$$v\left(p_{a.}Q_m\,, E_{m,}, s, c, m, n, b, x, Q_n\,, E_n\,, p_{n,}\right)$$

$$v(.) = \int_0^{\infty} e^{-\delta t} \left\{ \begin{matrix} [m\, p_{a.}Q_m\,(E_{m,}s) - m\, c(E_m) + n\, p_{n.}Q_n\,(E_{n,}x) - n\, b(E_n)](1 - G(t)) \\ +[n\, p_{n.}Q_n\,(E_{n,}x) - n\, b(E_n)]\; G(t) - RFg(t) \end{matrix} \right\} dt \tag{4.5}$$

Where $v(.)$ is the value function, δ is the discount rate. Equation (4.5) states that the fisher's expected discounted net profit is equal to the expected discounted profit from illegal fishing (the first and second terms) plus the expected discounted profit from legal fishing (the third term) minus the expected fine from violation (last term). The justification for using two period model that, with an infinite time horizon, as made by Akpalu, (2008) is that due to abject poverty, the illegal net may be transferred over generation.

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[6] The use of R is due to considerations such as corruption, as some fishers may escape paying a fine even if they are caught.

The probability of detection is modelled as a hazard rate, which is the conditional probability of having a spell length of exactly t, conditional on survival up to time t (Jenkins, 2005). Following Davis (1988), the probability of detection is equated to the hazard rate and set to be independent of time. Used in this context, the hazard rate is the probability that a law-breaking fisher be caught at time *t*, given that he escaped the police until time *t*. This probability is given by:

$$\Pr(E, m) = \frac{g(t)}{1 - G(t)} \tag{4.6}$$

Pr(.) is the probability of detection of a violator given that he/she has not been detected before; *E* is the constant enforcement effort of the regulator, *m*, as defined earlier is the rate of violation (e.g. number of months per year that the fisher fishes illegally). The survival function is $\left(1 - G(t)\right)$ and *E* and *m* are time-invariant. Then, we assume that the hazard rate increases with *m* at an increasing rate (i.e. $\frac{dPr}{dm} > 0$ $\frac{d^2Pr}{d^2m} > 0)$. This assumption of a convex relationship between probability of detection and violation rate is made following the standard DDM of Davis (1988). Furthermore, we assume that no fisher will be falsely detected, that is $Pr(0) = 0$.

$$\Pr(m) = \frac{g(t)}{1 - G(t)} = \frac{-d(1 - G(t)/dt}{1 - G(t)} \tag{4.7}$$

$$\Pr(m) = \frac{-dln(1-G(t)/dt}{d(t)} \tag{4.8}$$

Integrating both sides, we reach:

$$\int_0^t \Pr(m)\, dt - ln(1 - G(t)) \tag{4.9}$$

$$\ln\{1 - \mathrm{G(t)}\} = -\int_0^t \Pr(m)\, dt\ hence\{1 - \mathrm{G(t)}\} = \exp - \int_0^t \Pr(m)\, dt \tag{4.10}$$

Although regulated open access is the current management regime of JAR with no limit in catch or seasonal closure, the model assumes that the frequency of violation (*m*) is constant over time.

Then the values of the density and cumulative functions are:

$$\{1 - G(t)\} = e^{-Pr(m)t}; \;\; G(t) = 1 - e^{-Pr(m)t} \, and g(t) = \Pr(m)\, e^{-Pr(m)t} \qquad (4.11)$$

Substituting the values of $g(t)$ and $G(t)$ in equation (4.5) and assuming that all other variables are constant over time, we get the value function of each violator (integrating and rearranging of terms that results in (4.12) is explained in heading 1-Annexure A):

$$v(.) = \frac{(m\, p_{a.} Q_m \left(E_{m,} s\right) - m\, c(E_m) - RFPr(m)}{\delta + \Pr(m)} + \frac{n\, p_{n.} Q_n \left(E_{n,} x\right) - n\, b(E_n)}{\delta} \qquad (4.12)$$

The first term is the discounted profit from illegal fishing, while the second term is the discounted profit from legal fishing. Since the second term doesn't include illegal profit that depends on the rate of violation *(m)*, it will be dropped. Thus, the objective of the fisher will be to maximise the discounted illegal profit as follows:

$$v(.) = \frac{(m\, p_{a.} Q_m \left(E_{m,} s\right) - m\, c(E_m) - RFPr(m)}{\delta + \Pr(m)} \qquad (4.13)$$

Then, the optimal level of violation for each fisher is given by:

$$m^* = \arg max \;\; \frac{(m\, p_{a.} Q_m \left(E_{m,} s\right) - m\, c(E_m) - RFPr(m)}{\delta + \Pr(m)} \qquad (4.14)$$

Assuming an interior solution, the first order condition is given by:

$$\frac{dV}{dm} = \frac{[p_{a.} Q_m\,(.) - \; c(E_m) - RFPr_m\,](\delta + \Pr(m)) - Pr_m[m\, p_{a.} Q_m\,(.) - \; mc(E_m) - RFPr(m)]}{(\delta + \Pr)^2} = 0 \quad (4.15)$$

Where (Pr_m) is the differential of (*Pr*) with respect to (*m*). Condition (4.16) suggests that illegal fishing will be attractive up to the point where:

$$p_{a.}Q_m\,(.) - \,c(.) - RFPr_m = \frac{Pr_m[m\,p_{a.}Q_m\,(.) - \,mc(.) - RFPr(m)]}{(\delta + Pr)} \qquad (4.16)$$

Which is the point where the optimal level of illegal fishing is reached and beyond which net expected marginal benefits (left hand side) will be less than the discounted net marginal cost (right hand side) of illegal fishing. The fisher will never fish illegally (i.e. m=0) if:

$$p_{a.}Q_m\,(E_{m,}s) - \,c(E_m) - RFPr_m < 0 \qquad (4.17)$$

This condition is fulfilled for those who never violate (NV). This equation could only be positive if (*m)* becomes positive, i.e. the fisher starts to violate and thereby earns more money. The question becomes: why are fishers not willing to violate? There are two justifications for making such an inquiry. Firstly; it can be attributed to the influence of some other important non-monetary reasons preventing fishers from violating regulations (i.e. normative factors) such as moral beliefs. Secondly, fishing is not likely to be the main source of income for this group.

Note that the condition in equation (4.17) is independent of the discount rate, but depends on the expected marginal fine. However, in a poor institutional environment with weak enforcement, condition (4.17) is highly likely to be positive. For instance, in a community of chronic violators, we can deduce from equation (4.17) that violators will totally switch to illegal fishing if:

$$p_{a.}Q_m\,(.) - \,c(.) - RFPr_m \geq \frac{Pr_m[m\,p_{a.}Q_m\,(.) - \,mc(.) - RFPr(m)]}{(\delta + Pr)} \qquad (4.18)$$

This condition is fulfilled for those who are full-time violators (CV).

4.3 The effect of key determining factors on the optimal violation rate

This section employs the method of comparative static to explore direction of the effect of each factor on the rate of violation. The first order equilibrium condition is calculated to derive comparative static results on the effects of various factors on the frequency of violation using the implicit differential rules in equilibrium (Chiang, 1984). These results will help to understand the nature of determining effects of some factors of policy relevance on the optimum value of violation, i.e. frequency of violation.

Let the first order conditions of equation (4.15) be denoted by K and use it to derive the comparative static of the model with respect to its parameters (See detailed derivation of results in Heading 2-Annexure A).

(1) Effect of probability paying the fine (enforcement)

$$\frac{dK}{dR} = -\delta F Pr_m < 0 \qquad (4.19)$$

There is no doubt that equation (4.19) has a negative value, given the fact that Pr_m , F and δ are all positive. This result implies that violation rate/frequency m^* decreases with an increase in the probability of paying the fine R.

(2) Effect of level of fine F

$$\frac{dK}{dF} = -\delta R Pr_m < 0 \qquad (4.20)$$

The same argument used in equation (4.19) applies to equation (4.20) suggesting that frequency of violation m^* decreases with an increase in the amount of fine (F).

(3) Effect of probability of detection Pr(m)

$$\frac{dK}{dPr(m)} = [p_{a.}Q_m(.) - c(E_m) - RFPr_m] + RFPr_m = \pi(.)_m + RFPr_m = 0 \qquad (4.21)$$

For condition (4.21) to give the expected negative sign (negative impact of probability of detection on violation rate), the expected marginal fine for the violation has to be greater than the discounted marginal gain from violation. This will hold true for larger values of the expected penalty, implying that the higher the probability of detection, the lower is the frequency of violation.

(4) Effect of discounting the future δ

$$\frac{dK}{d\delta} = p_{a.}Q_m(.) - c(E_m) - RFPr_m > 0 \qquad (4.22)$$

The positive result of the specification in (4.22) is implied by the condition of optimality derived in equation (4.16) for violating fishers, e.g. for $m > 0$. Accordingly, this result suggests that violation rate increases with higher discount rates. That means the less important the future is for the violators, who prefer a given amount of money today than to having the same amount in the future.

(5) Effect of price of / returns to illegal catch P_a

$$\frac{dK}{dP_a} = Q_m(E_{m,}s)(\delta + \mathrm{Pr} - \mathrm{Pr}_\mathrm{m}) \geq 0 \qquad (4.23)$$

For equation (4.15) to be optimal the following condition must be hold:

$$\delta + \mathrm{Pr} > \mathrm{Pr}_\mathrm{m}$$

This implies non-negativity of result (4.23) suggesting that frequency of violation increases with higher prices of (returns from) illegal (mixed) catch.

(6) Effect of fixed cost of the illegal net c

$$\frac{dK}{dc(.)} = -\delta - \mathrm{Pr} + \mathrm{mPr_m} = ? \tag{4.24}$$

Result (4.24) is indeterminate and would give the expected negative effect of a rise in the cost of acquiring the illegal net if the following must hold:

$$\mathrm{Pr_m} < \frac{\delta + \mathrm{Pr(m)}}{\mathrm{m}} \tag{4.25}$$

Condition (4.25) simply requires that the incremental risk of being caught (marginal chance of detection) should be less than the average expected gains from not violating (opportunity cost of waiting for next period plus probability/opportunity of being caught) per violation attempt.

The analytical results of this extended DDM using frequency measures are compared with the results of earlier empirical studies in Table 4.1. It is clear that dynamic formulations have important advantages over static models as they could control for the effects of key factors such as discounting the future, costs and prices. Analytical results derived with the extended DDM, which uses frequency measures, confirm the findings of the empirical DDM using intensity measures for the effects of key factors. These factors are probability of fining (enforcement), level of fine and discount rate.

The conclusion from the static model of Becker (1968) and other studies that used static formulations is that a penalty (fine) should be high to deter violation. On the other hand, studies that applied the dynamic deterrence model suggest that crime is more likely to be deterred by increasing the probability of detection than by raising the fine (Akpalu, 2008; Davis, 1988; Lueng, 1991). In this study for probability of detection to deter violation expected marginal fine should outweight expected discounted gain from violation.

Table (4.1): Summary of the comparative static' analyses for different models

Determinants of compliance/violation using intensity or frequency measures	**Static models using frequency measures A**	**Dynamic models using intensity measures C**	**Dynamic models using frequency measures (this study)**
Probability of fining (R)	Negative	Negative	Negative
Level of fine (F)	Negative	Negative	Negative
Probability of detection	Must be less than the fine [B]	Expected marginal fine must be higher than marginal profit from violation	Expected marginal fine must be higher than marginal profit from violation
Discount rate (δ)	Not included	Positive	Positive
Price of / income from illegal catch	Not included	Undetermined	Positive
Fixed cost of illegal fishing	Not included	Undetermined	Undetermined
Normative factors	Positive/negative	Positive	Not included

A. This group includes Furlong (1991), Kuperan and Sutinen (1994 and 1999), Hatcher et al. (2000) , Hatcher and Gordon (2005), Kuperan and Sutinen (1998), King and Sutinen (2010).
B. Except for Furlong (1991).
C. This group includes Lueng (1994), Davis (1988), and Akpalu (2008).

4.4 Summary

This chapter presented the DDM analytical framework adapted in the study to investigate the importance of choosing the suitable method of measuring violation rates. It suggests that due to a number of factors related to institutional and market failure, frequency rather than intensity measures are more feasible and policy relevant measures of noncompliance with regulations, particularly in artisanal fisheries of developing countries. Using frequency as a measure of violation rate provides the opportunity of capturing the direct link between violation rates and seasonality of illegal fishing (e.g. months of active breeding when quantities of small fish are high, which encourages illegal fishing). Use of frequency helps to classify fishers into categories of violators. These categories will help policy makers and managers design policy measures and instruments suited for each group. In spite of these apparent advantages frequency has been used only in static deterrence models and studies that employed DDM have so far only used intensity of violation measures to analyse noncompliance with fishery regulations.

Accordingly, this chapter extends the two periods dynamic deterrence model (DDM) to use frequency instead of intensity of noncompliance as a measure of violation rate. The method of comparative static is employed to derive analytical results on the sensitivity of optimal violation to a number of key factors of high relevance to compliance with regulations designed to protect against over-fishing. Analytical results obtained with this extended DDM confirm the findings of earlier empirical studies employing alternative static and dynamic formulations and reveal more interesting economic meaning of modelled relations. The study shows that in the artisanal fishery industry in developing countries, violation rates are bound to be high. This is the case, given that probability of detection, enforcement and levels of fine are typically low and poverty levels lead to high impatience about the future (social discounting). Nevertheless, the relative magnitude of the effects of each of these factors on compliance with regulations remains an important empirical question that requires further investigation for prioritisation of policy actions. The chapter however, provides a general theoretical model that could be valid and potentially applicable to developing countries with similar fishing circumstances of regulated open access such as the one modelled here.