Why do fishermen comply with regulations? The role of preferences

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Introduction

Compliance with rules and regulation is a necessary condition for effective resource management. It is therefore important to improve our understanding of the motivation of resource users to obey or violate certain rules and regulation. Investigating compliance is challenging for two reasons (Boonstra et al., 2016). First, only the number of detected violations can be directly observed, not the motivation to comply or the temptation to violate. Second, the number of detected violations depends on the probability of being observed, so that any attempts to measure compliance will influence the tendency to comply. Therefore, existing evidence on compliance is often qualitative or stems from self-reported surveys. In spite of these difficulties, this research has consistently and successfully shown how compliance depends on various factors, such as the benefits of a violation, the expected penalty, but also the intrinsic motivation to comply and the social context (Kuperan & Sutinen, 1998; Hatcher & Gordon, 2005; Viteri & Chàvez, 2007; Eggert & Lokina, 2010).

The objective of this book chapter is to provide quantitative insights on the motivation to comply by analyzing data from a large mail survey conducted among Norwegian fishers. First, we unpack the general notion of compliance by investigating norm-specific motivations and attitudes. We asked fishers about the perceived severity of various violations, whether violating is acceptable in certain circumstances, and whether respondents violate a regulation more or less than the average fisher. The survey questions are then combined with data on risk, time, and social preferences obtained from incentivized lottery experiments. The second part of our study analyzes the determinants of compliance, and particularly the role of economic preferences. We use a standard regression framework to explain compliance attitudes and behavior with economic preferences. In addition, we use a machine learning algorithm to explore the importance of wider contextual factors and potential nonlinear relationships.

This book chapter draws on the economic literature on rational compliance (Becker, 1968) and the role of intrinsic motivation and social norms

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to comply (Acheson & Gardner, 2010; Boonstra et al., 2016). First, the economic literature on compliance is deeply rooted in the work of Gary Becker, who established the idea of a "rational criminal" (Becker, 1968). The idea is that a criminal act is no different than any other economic action where the expected benefits are weighed against the expected costs. Typically, detection is probabilistic, and non-compliance is thus risky. Hence, the risk preferences are expected to play an important role in determining whether a violation occurs. If the penalty implies an exclusion from the resource grounds (Copeland & Taylor, 2009) or other, potentially reputational costs that occur in the future, time preferences are expected to matter as well. While the theoretical literature predicting non-compliance in fisheries is clear on these factors (Nøstbakken, 2008), the empirical literature is very sparse in this respect. In fact, to the best of our knowledge, the two other papers that directly relate compliance and economic preferences are Eggert and Lokina (2010) and Brick et al. (2012).

Eggert and Lokina (2010) collect data from artisanal fishers at Lake Victoria, Tanzania, and find that stated measures of risk aversion are positively related to violations. This counter-intuitive finding arises most likely because risk aversion is correlated with subsistence fishing. Respondents living at the poverty line may have no other option than to violate existing regulations in order to secure food and income. Brick et al. (2012) report the results from a survey in South-African fishing communities. They find a positive correlation between risk aversion and compliance behavior. Here, we conduct an incentivized economic experiment among fishers in a highly developed country (Norway). We contribute to the literature by investigating how elicited time and risk preferences correlate with the tendency to violate rules. In line with theoretical predictions, we find that individuals who are more risk averse, report to violate less. This is also in line with the work of Block and Gerety (1995), who use experiments to study whether there are differences in relative responsiveness to changes in the detection risk and the severity of the punishment between criminals and the general population. Their experimental results confirm that criminals are relatively less sensitive to the detection risk, in line with criminals having relatively low aversion to risk.

Overall, however, we find that fishers are rarely motivated by expected penalties, and mostly intrinsically motivated by the universal notion that "one should follow the law". Indeed, while the Becker model is powerful, it falls short of grasping all social complexities of human decision making, particularly the intrinsic motivation and how social norms to comply may be powerful mechanism to deter violations. In principle, these notions are by no means incompatible with a rational actor model and could enter as potential (psychological) costs of non-compliance.

There are several studies that have followed this approach and that document the importance of non-pecuniary factors such as the perceived legitimacy of the regulations, social interactions with peers, and moral considerations (Kuperan & Sutinen, 1998; Eggert & Ellegård, 2003; Hatcher &

Gordon, 2005; Viteri & Chàvez, 2007; Eggert & Lokina, 2010; Jagers et al., 2012). Interestingly, Eggert and Ellegård (2003) find a clear difference in the importance of social/moral considerations versus economic consideration depending on the scale of operation in the survey of Swedish fishers: the operators of large, highly capitalized vessels are much less confident that co-management approaches will help to regulate fisheries and put their trust on formal punishment and official monitoring to deter violations. This is in line with findings from Hatcher and Gordon (2005) who survey UK fishers about quota violations and find that non-economic considerations are relatively unimportant in this industrialized fishery.

The decision base is typically complex and multi-faceted. As many individuals are thought to be conditionally compliant, the intrinsic motivation to comply will depend on how widespread such behavior is. We therefore add to this literature by exploring how economic preferences (regarding risk and time) may interact with social value orientation (e.g., altruistic, individualistic).

In addition, we ask individuals about their primary motivation to obey certain rules and regulations. We consider formal violations (e.g., illegal equipment) and informal violations (e.g., sharing false information). We find that the fear of formal punishment plays only a minor role. Instead, as already mentioned, a main motivation appears to be of deontological nature (i.e., fishers are motivated by the universal rule that one should follow the law). Interestingly, also the development of the stock is an important reason to comply with certain regulations. This is remarkable, given the scale of the Norwegian fisheries where the actions of individual fisher have a negligible impact on the resource base.

Material and methods

Web-based survey and experiment

To learn more about compliance behavior and motivations in fisheries, we have conducted a large mail survey among Norwegian fishers. We sent out invitations in spring 2014 and directed participants to a website where they would answer incentivized and non-incentivized choice questions. 253 fishermen responded, which is a response rate just above 10%. We also elicited answers from a control group of 413 respondents randomly picked from the public registry but do not use these answers in this book chapter. The respondents represent the entire Norwegian coast, vessel owners and crew, small and large boats, and all age groups (Figure 5.1). The sample, as the population of Norwegian fishers, consists almost entirely of males (98.4%).

The survey was made up of three blocks. First, it started with a set of questions on the demographic and socio-economic background of the respondents. Second, the survey contained several lottery-based experiments to measure individual preferences. In this part, we elicited risk and time

Figure 5.1 Birth year and geographical distribution of respondents.

preferences as well as prospect theory parameters, such as loss aversion by following the methodology used by Tanaka et al. (2010). Furthermore, we elicited social preferences by using the ring-measure as proposed by Liebrand and McClintock (1988). The third part of the survey contained fishery-specific questions on the fisher's background, the fishery they operate in, their investments and ownership, and their expectations for the future of the fisheries (see Table 5.A1 for some of these variables). Importantly, this part contained three sets of questions about non-compliance.

First, we asked about the fisher's attitude toward various rules and regulations. Specifically, we asked whether it can be justified to (1) employ or offer unreported ("black") labor, (2) use illegal gear, fish outside of the legally mandated seasons or areas, (3) spread wrong information to other fishers, (4) catch fish below minimum size, (5) not report fish sales, (6) discard fish, (7) under- or mis-report catch, and (8) to not share valuable information with other fishers. For each of these, respondents could answer "never", "sometimes", or "usually".

Second, for these eight types of violations, we asked about the main reason for fishers to comply. We offered the following choices: "Fear of formal punishment", "One should follow the law", "Stock development and future income", "It is unfair relative to others", "It damages my reputation among fishers", and "other". The decision to violate or follow a norm is multifaceted and several aspects play a role. This is why we asked about the *main* reason and allowed respondents to pick only one option. Moreover, asking about the main reason to follow a given norm allows us to analyze norm-specific differences in motivations as well as the variability of motivations across and within respondents.

Third, for three violations, we asked whether the respondent's think they violate "more, "less" or "about the same" as the average. Here, we limit this question to the three regulations where we expected the highest degree of violations namely, "discards", "minimum size regulations" and "unreported fish sales".

Measurement of prospect theory parameters

The experiments are pairwise-lottery-based experiments in a form that is similar to that of Tanaka et al. (2010). We employ a prospect theory framework of Kahneman and Tversky (1979) as opposed to standard expected utility to estimate respondents' preferences. Consider two mutually exclusive payoff outcomes, x and y, where $x > y$ and $x > 0$. The probability of outcome x is p. We assume agents' values of prospects are $\pi(p)v(x) + 1 - \pi(p)\ v(y)$. The function $\pi(\cdot)$ is the probability weighting function. Specifically, following Tanaka et al. (2010), we assume $\pi(\cdot)$ takes the form of a one-parameter weighting function that is axiomatically derived by Prelec (1998), i.e., $\pi(p) = e^{-(-\ln(p))^{\alpha}}$. The probability weighting function is linear if $\alpha = 1$ as in standard expected utility theory. The function is S-shaped if $\alpha > 1$ (and inverted S-shaped if $\alpha < 1$).

In the prospect value function, $v(\cdot)$ is the agents' value of a certain payoff. We assume it takes the form of $v(x) = x^r$ for $x > 0$ and $v(x) = -\lambda(-x)^r$ for $x < 0$. Hence, r is the measure of the concavity of the agents' utility function, and our measure of the agents' degree of risk tolerance. A higher r means the agent is more tolerant to risk. The parameter λ is the measure of loss aversion, and a higher λ means more loss averse. To sum up, we assume respondents have the following form of values:

$$\begin{aligned} &e^{-(-\ln(p))^{\alpha}} x^r + \left(1 - e^{-(-\ln(p))^{\alpha}}\right) y^r, \quad \text{for } x > y > 0 \\ &e^{-(-\ln(p))^{\alpha}} x^r - \lambda\left(1 - e^{-(-\ln(p))^{\alpha}}\right)(-y)^r, \text{for } x > 0 > y \end{aligned} \tag{1}$$

Payoffs used in our experiments are shown in Table 5.A2. In each experiment, we ask respondents in which situation they would switch from lottery A to lottery B. They also have the options to always choose lottery B over A and to never switch from A to B. We jointly estimate r, α and λ using respondents' choices in the first three experiments. The payoffs are carefully designed such that any combination of choices in these three experiments jointly determines a unique set of intervals of the three parameters.

The estimation steps are as follows. First, the first two experiments do not involve losses, hence we can jointly estimate r and α using Experiments 1 and 2. For each combination of choices in the first two experiments, (C_1, C_2), we can find a unique combination of value intervals of r and α that will induce a respondent to make such choices.

Next, after we have estimated r and α, we can estimate each respondent's value of λ given their choices in Experiment 3.

Measurement of time preferences

To elicit participants' time preferences, participants are asked to choose between receiving money today and receiving money in eight months for 12 choice situations. While in the first situation the monetary amounts are identical, the amount to be received in the future increases, reflecting an increasing discount rate δ. Akin to the three experiments before, participants are asked to choose a range of rows in which they prefer A to B, while preferring B to A for the rest. Participants were also given the option to choose either A or B for all rows. However, in theory, any individual with a positive discount rate would prefer A over B in situation 1. Then for some later situations, they may or may not "switch" from A to B. Participants who switch to B later have higher discount rates.

Our method to calculate the implied discount rate for individual i is as follows. Let B_j denote the payoff of situation j of choice B, $j = 1,2,...,12$. The present value of B_j is thus $PV\left(B_j\right) = \frac{B_j}{\left(1+r_i\right)^{8/12}}$. If the participant preferred A over B in situation j and preferred B over A in situation $j+1$, it must imply that $\frac{B_j}{\left(1+r_i\right)^{2/3}} < 700 < \frac{B_{j+1}}{\left(1+r_i\right)^{2/3}}$, or equivalently, $\left(\frac{B_j}{700}\right)^{3/2} - 1 < r_i < \left(\frac{B_j}{700}\right)^{3/2} - 1$. We use the upper limit of $r_i = \left(\frac{B_j}{700}\right)^{3/2} - 1$ as an estimate. For example, if a participant chose A over B in situation 1 and chose B over A in situations 2–12, we estimate his implied discount rate as $r_i = \left(\frac{712}{700}\right)^{3/2} - 1 = 0.0258$. Further, we assume that participants who always choose B over A have a discount rate of zero, and that those who always choose A over B have discount rates of 0.35, which are the upper and lower bounds.

Measurement of social preferences

To elicit participants' social preferences, we asked participants to make choices in 16 situations. In each situation, each participant (dictator) chose between two combinations of his/her own payoff and the payoff of another participant (recipient) who was matched randomly. The dictator and the recipient were anonymous to each other. The payoffs of all situations are shown in Table 5.A3.

We calculate the participants' types of social values using the ring measure following Liebrand and McClintock (1988). The calculation process is as follows. Say in situation $t \in \{1,2,\ldots,16\}$, that participant i chose a combination that gave her or him a payoff of $S_{i,t}$, while the recipient's payoff was $O_{i,t}$. Her or his total payoff in all 16 situations is then $S_i = \sum_{t=1}^{16} S_{i,t}$, while the recipient's total payoff is $O_i = \sum_{t=1}^{16} O_{i,t}$. The maximum payoff that one could give to oneself or the other person is 500. Therefore, we use the variables $S_i/500$ as a proxy for individualism and $O_i / 500$ as a proxy for altruism.

Regression model

In this study we want to find out what can explain observed compliance motivations and reported behaviors. In other words, we seek to find key underlying determinants of compliance attitudes. To assess whether economic preferences affect compliance attitudes and behavior, we focus on violations regarding (i) discarding and (ii) minimum size regulations. These two sets of violations are particularly interesting because of the direct impact on stock sustainability, but also because of their relevance to fisheries management and control activities.

We create binary response variables from the answers to our survey questions on compliance attitudes and behavior. Specifically, we analyze whether fishers state that they violate a specific regulations less than average ($y = 1$) or same/more than average ($y = 0$), and we analyze whether fishermen state that violating a specific regulations can never be justified ($y = 1$) or sometimes/usually be justified ($y = 0$).

We set up the following probit regression model to analyze how economic preferences and a set of covariates explain compliance:

$$\Pr\left(y_{ijz} = 1\right) = \alpha_j + \boldsymbol{\beta_j} * \boldsymbol{X_{ijz}} + \boldsymbol{\gamma_j} * \boldsymbol{V_{ijz}} + \varepsilon_{ijz} \qquad (2)$$

where i denotes respondent and j denotes whether we analyze violation behavior ($j = 1$) or justification ($j = 2$) of rules with respect to discarding ($z = 1$) or minimum size limits ($z = 2$). $\boldsymbol{X_{ijz}}$ and $\boldsymbol{V_{ijz}}$ are vectors consisting of the respondent's economic preferences and control variables, respectively.

Machine learning algorithm

As our survey collected a large amount of information about fishermen's characteristics and attitudes, we have many covariates that could potentially explain whether participants responded that they would comply with rules and regulation. This poses two challenges to a standard regression analysis, as outlined before. First, it is not obvious which covariates to include and how to select the most relevant ones. Second, it may be interesting to explore how survey answers are correlated (e.g., self-reported violation and underlying reasons to respect certain rules), but it would be problematic to include those variables in a regression framework as the answers are not exogenous. This exercise is better suited for modern machine-learning algorithms, which we use to supplement the regression analysis.

While regression models estimate the effect of each variable that the researcher includes into her model, independently of whether the variable explains variation in the data, machine learning algorithms, such as random forests, approach the question from a different angle. Random forests essentially work by aggregating information from many component classification trees, where each classification tree is based on a random subset of the data, considering at each branch a random subset of the predictor variables.

Internally dividing the data into a training set and a testing set ('out-of-bag data') for each tree allows to assess the significance of each predictor: it is calculated by comparing the classification performance of a given tree on the 'out-of-bag' data where the covariate values of that predictor is or is not scrambled. The mean decrease Gini for that variable then measures by how much the Gini index decreases on average, when the predictor is removed. The Gini index is a measure of "node purity" and tells how cleanly the data is divided over categories at a given split. The larger the mean decrease in Gini index, the more important is the variable.

A key strength of random forests is that it can handle situations with many explanatory variables. We therefore apply the algorithm to the full set of potential predictors in the data and then use the iterative procedure implemented in the R-package VSURF (Genuer et al., 2016), for variable selection.

Random forests do not return numerical values that summarize the effect of the predictor on the response variable. To obtain some deeper insight into how the given variables affect how a respondent would typically be classified, we present partial dependence plots for key variables. Partial dependence plots estimate the marginal functional response between a predictor and the predicted outcome. Hence, for a given value of the predictor, we calculate its mean effect on the classification probability over the range of all possible values of the other covariates, which then produces a possibly non-linear curve for the selected predictor.

Results

In this section, we first present the results from the survey by giving an overview of the respondents' characteristics and exploring their compliance attitudes and norms. Second, we analyze the determinants of compliance attitudes by presenting the results from the machine-learning algorithm.

Respondent's characteristics and compliance attitudes

Table 5.1 gives summary statistics for key variables of the sample (253 observations). In addition, we have information on the respondent's current place of living, their home community and region, where they were born, and to which regulatory group their vessel belongs.

Respondents are between 18 and 77 years old and almost exclusively male (Table 5.1). They have on average 2.22 children and 2.92 siblings. Interestingly, 55% of the fishermen come from families where at least one of the parents have been fishers, but only 17% think that their children will be fishers. The variable "Tenure" denotes how many years the respondent has already spent in the industry (between 0 and 64 years), the variable "Vessel owner" is a dummy which takes the value one if the respondent owns the vessel on which she or he works, and the variable "Income" gives the income bracket for the respondent.

Table 5.2 shows the elicited risk, time and social preferences. The variables "Altruistic" and "Individualistic" give the social value orientation of the respondents as elicited using the ring measure (where a higher value means a more altruistic/individualistic posture). Rows one to four reports the means and standard deviations of the four economic preference parameters, r, α, λ and δ, elicited using the experiments described above. Our estimated mean values of r and α (0.86, 0.61) are close to the estimated values of (0.59, 0.74) by Tanaka et al. (2010) for Vietnamese villagers, and the (0.48, 0.69) by Liu (2013) for Chinese farmers. Our estimates thus suggest that Norwegian fishers are more risk-tolerant than Vietnamese villagers and Chinese farmers. Our estimated mean value of λ is 2.05 and close to the 2.25 estimated by Tversky and Kahneman (1992), yet lower than the 2.63 of Tanaka et al. (2010) and 3.47 of Liu (2013). Although our subjects of Norwegian fishers differ from subjects in the above cited studies in terms of wealth, culture, profession, etc., our estimated preference parameters are reasonably close.

Table 5.1 Summary Statistics

Variable	*Mean*	*Std. Dev.*	*Min.*	*Max.*
Age	47.23	12.805	18	76
Gender (male=1)	0.98	0.125	0	1
Number of kids	2.22	1.596	0	11
Number of siblings	2.92	1.692	0	11
Parent fisher	0.55	0.498	0	1
Expect children fisher	0.17	0.38	0	1
Tenure	26.03	14.575	0	64
Vessel owner	0.65	0.478	0	1
Income	11.89	4.139	1	18

Table 5.2 Elicited Risk, Time and Social Preferences

Statistic	*Mean*	*St. Dev.*	*Min*	*Max*
r	0.86	0.52	0.05	1.58
α	0.61	0.27	0.08	1.48
λ	2.05	3.09	0.05	11.66
δ	0.11	0.11	0.00	0.29
Altruistic	0.10	0.30	−0.72	0.82
Individualistic	0.59	0.36	−0.38	1.00

Can it be justified to violate a rule or regulation?

The first compliance related question of the survey was whether it could be justified to violate a rule. We asked this question for an array of specific formal regulations and informal norms. Figure 5.2 shows the relative share of respondents that have, for each rule, answered "never", "sometimes" or "usually".

We see that compliance with rules and regulations is not absolute. Rather, rules and regulations are social constructs that are negotiable, and there may be circumstances and reasons when violating a norm can be justified. Whether it can be justified to violate a given norm depends on the norm itself. This difference is surprisingly large: while 90% of the respondents state that it is never justifiable to violate gear or area restrictions, more than 50% state that it is sometimes or usually justified to violate reporting regulations.

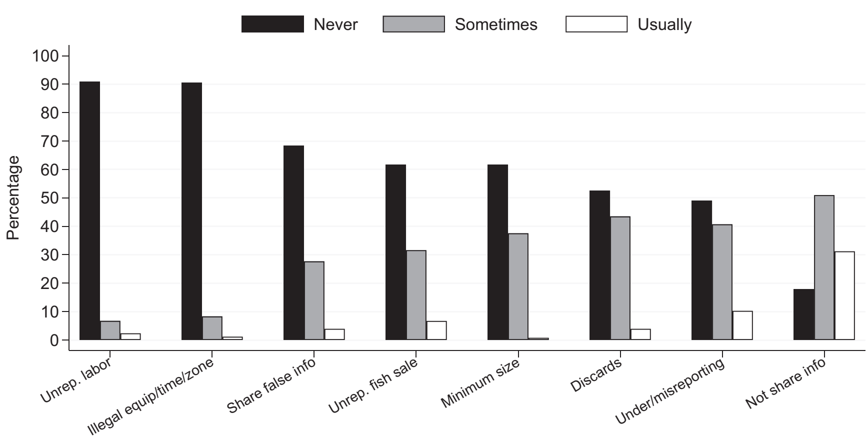

Figure 5.2 Survey responses to Q1: Can the violation be justified?

While we see strong differences between the various norms and regulations, these differences follow the different classes: while the informal rule that one should not hold back valuable information is the weakest, violations of the corresponding informal norm that one should not spread wrong information is less acceptable than many formal rules. Similarly, the non-fishery-specific rule that one should not employ unreported labor is in fact the strongest norm from this set.

Why comply with rules and regulations?

The stated motivations for why the fishers comply with the various rules and regulations are shown in Figure 5.3. Maybe surprisingly, the general notion that "one should follow the law" is the main reason for compliance, while "fear of formal punishment" is less important. The second most important reason for complying are considerations about the sustainability of the fishery and the future development of fish stocks. Finally, "Other" reasons includes concerns about the reputation among fellow fishers, and play only a subordinate role.

Figure 5.3 shows that the reasons for compliance are also norm specific. This is particularly evident for minimum size regulations and the discard ban, which makes sense as violating these rules has the most direct negative effect on the fish stocks.

Compliance relative to average?

While it is not possible to obtain direct and reliable information on the actual violations of respondents in a simple survey, we did ask about the compliance

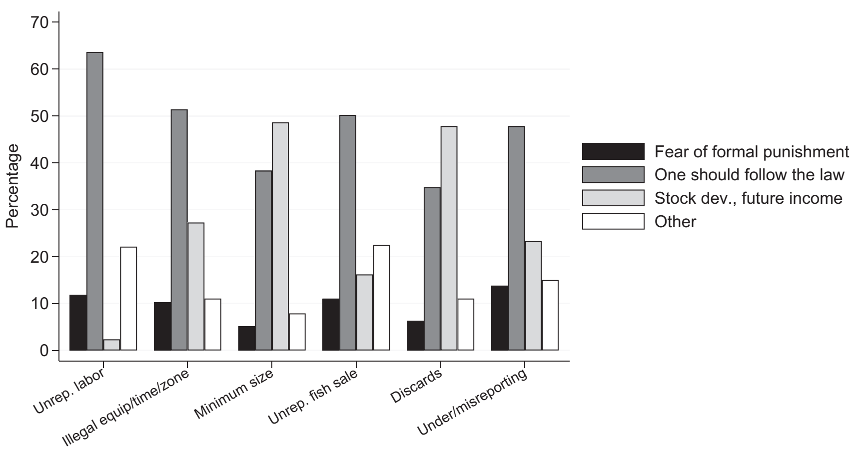

Figure 5.3 Survey response to Q2: Main reason for compliance?

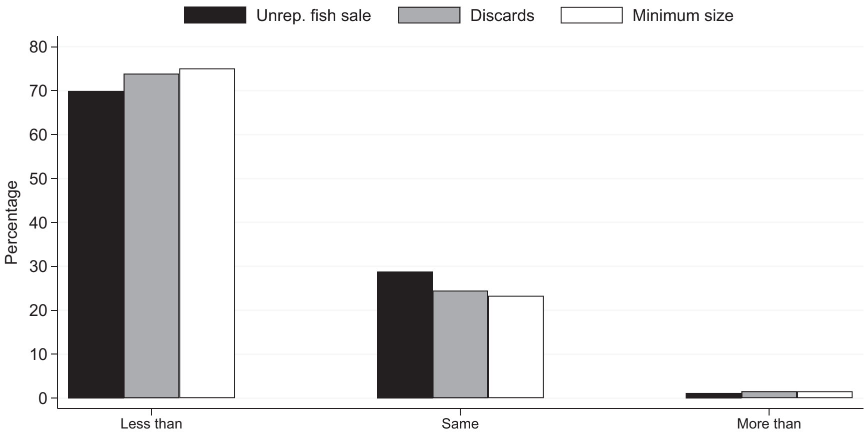

Figure 5.4 Survey responses to Q3: Assessment of own versus average compliance behavior

behavior relative to the average. Figure 5.4 shows that the vast majority of respondents think that they violate less than the average. This is in line with surveys among car drivers that find that most respondents think they drive better than the average. These effects may be due to over-confidence, an interviewer demand effect or to sample selection. However, to the extent that such a selection bias indeed prevails, it does not matter for the analysis here and in the subsequent section, as we are interested in explaining relative differences.

In line with the answers to the survey question about how justifiable different violations are (Figure 5.2), of the three violations we asked about in this part of the survey, violating the discard ban is most acceptable and has the highest share of respondents who state they violate about the same or more than the average.

Regression results

In the following, we present the regression results from our analysis of which variables explain whether respondents state that they violate the discard ban or minimum size regulations less than the average, or that such violations can never be justified. First, we look into the self-reported tendency to violate, i.e., whether individuals indicated they would violate more or less than the average (see Table 5.3). Above all, we find that economic preferences and covariates tend to explain little, as coefficients are often small and insignificant. The coefficient of the probability weighting parameter α is positive, albeit only significant at a 10% level, meaning that those who put less emphasis on small probabilities (small α) tend to state that they violate less than

Table 5.3 Probit Regression for the Question Whether Respondents Think They Violate Rules for Discarding and Minimum Size Limits Less ($y = 1$) or More ($y = 0$) than Average

	Low discard violation		*Low min. size violation*	
	(1)	*(2)*	*(3)*	*(4)*
Risk tolerance	−0.092	−0.082	−0.186	−0.157
	(0.178)	(0.183)	(0.183)	(0.185)
Prob weighting	0.641*	0.612*	0.667*	0.622*
	(0.342)	(0.348)	(0.363)	(0.372)
Impatience	0.453	0.450	−0.369	−0.470
	(0.669)	(0.666)	(0.631)	(0.632)
Loss aversion	0.054*	0.055*	−0.003	−0.001
	(0.032)	(0.033)	(0.031)	(0.031)
Altruism	−0.298	−0.309	−0.145	−0.158
	(0.286)	(0.294)	(0.280)	(0.290)
Individualism	0.110	0.127	0.083	0.192
	(0.235)	(0.248)	(0.242)	(0.258)
Age		0.004		−0.004
		(0.012)		(0.012)
Tenure		−0.007		0.005
		(0.010)		(0.011)
Income		−0.122		−0.262**
		(0.115)		(0.121)
Vessel owner		−0.012		−0.152
		(0.190)		(0.196)
Constant	0.046	0.387	0.451	1.226**
	(0.299)	(0.575)	(0.311)	(0.611)
N	253	251	253	251

average. Also, loss aversion is positively correlated with stating that one violates less than average, but only for discarding, and it is only significant at the 10% level. Intuitively, it makes sense that those who report that they violate less are more loss averse. Finally, income is negatively correlated with stated violations, although only significant for minimum size violations, meaning that those who have higher income are less likely to report that they violate less than average.

Turning to the question of what explains whether violation can be justified (Table 5.4), we notice again that economic preferences and covariates tend to be insignificant. Again, loss aversion is positive and significant at a 10% level for discarding. Also, income is negatively correlated with stating that violating that minimum size limits can never be justified. We now find that individualism is negatively correlated with saying that violating discarding regulations can never be justified, which makes intuitive sense. Note that the probability weighting function, which is significant in Table 5.3, is not significant when explaining justification of violations. Overall, we conclude that the link between economic preferences and compliance attitudes is rather weak. While the relationships that show up significant are plausible,

Table 5.4 Probit Regression for the Question Whether Violating Discarding and Minimum Size Limits Can be Justified ("never" is Coded as $y = 1$ and the Answers "Sometimes" or "Usually" is Coded as $y = 0$)

	Never Justify Discard		*Never Justify Min. Size*	
	(1)	*(2)*	*(3)*	*(4)*
Risk tolerance	0.148	0.115	0.081	0.088
	(0.166)	(0.168)	(0.170)	(0.173)
Prob weighting	0.147	0.098	0.329	0.292
	(0.308)	(0.310)	(0.309)	(0.318)
Impatience	−0.027	−0.051	0.509	0.425
	(0.585)	(0.593)	(0.625)	(0.637)
Loss aversion	0.066**	0.065**	0.029	0.026
	(0.027)	(0.028)	(0.028)	(0.029)
Altruism	0.310	0.350	0.234	0.326
	(0.271)	(0.276)	(0.266)	(0.280)
Individualism	−0.522**	−0.584**	0.035	0.139
	(0.229)	(0.246)	(0.227)	(0.243)
Age		−0.001		0.004
		(0.011)		(0.012)
Tenure		0.001		0.005
		(0.009)		(0.010)
Income		−0.064		−0.330***
		(0.110)		(0.120)
Vessel owner		0.149		−0.060
		(0.182)		(0.183)
Constant	−0.006	0.180	−0.118	0.420
	(0.277)	(0.552)	(0.282)	(0.569)
N	253	251	253	251

they tend to be only weakly significant and are often only significant for one of the violations.

Machine learning results

In this subsection, we present the results of our Machine learning algorithm. First, we report which variables are important factors in explaining the variance of key survey questions. Table 5.5 shows the ranking of the explanatory variables (the largest decrease in 'Mean Gini index') for the question of whether respondents violate the discard ban as much or more than average (left column) or less than average (middle column). The 'Mean decrease Gini' indicates how much of the explanatory power is lost if we omit a variable. The out-of-bag estimate of the classification error rate is 29.6%, which indicates that a large part of the variation remains idiosyncratic and cannot be well explained by the available covariates. We find that 'Age' and 'Tenure' are the most important variables, followed by 'Probability weighting' and 'Loss aversion'. Interestingly, 'Age' and 'Tenure' had

Table 5.5 List of Most Important Variables that Explain Who States to Violate Discard Regulations Same/More or Less than Average, Ordered by Decreasing Importance

	Same/More	*Less*	*Mean Decrease Gini*
Age	−4.33	17.23	17.39
Tenure	−5.51	13.52	16.33
Probability weighting	11.49	6.81	14.57
Loss aversion	1.07	12.10	14.40
Reason for illegal sales	0.45	8.42	8.33
Reason for spreading wrong info	−5.24	4.86	7.21
Reason for black labor	−5.19	14.48	6.63
Reason for violating size limits	−2.65	13.26	6.51
Reason for discarding	−7.71	12.90	6.17
Vessel owner	−4.09	6.11	3.21

coefficients close to zero and were insignificant in the regression framework but are identified to be important here. 'Probability weighting' and 'Loss aversion' were also important variables in the regression framework.

Figure 5.5 shows the partial dependence plots for whether respondents state that they violate the discard ban less than average. First, we find that the relationship with age is highly non-linear, where fishers around the age of 35 are least likely to state that violating discarding rules can never be justified. Second, the propensity to violate less than average is increasing with tenure. Note that there are few observations of tenure beyond 40 years, so the drop visible in the plot should be interpreted with caution. Third, we see that individuals with a small α, those who overweight small probabilities the most, are much more likely to state that violations can never be justified. Also, with increasing values of α beyond the mean (0.61), individuals are more likely to state that violation can never be justified. Fourth, a higher degree of loss aversion, where the mass of observations takes a value between 0 and 2, implies a

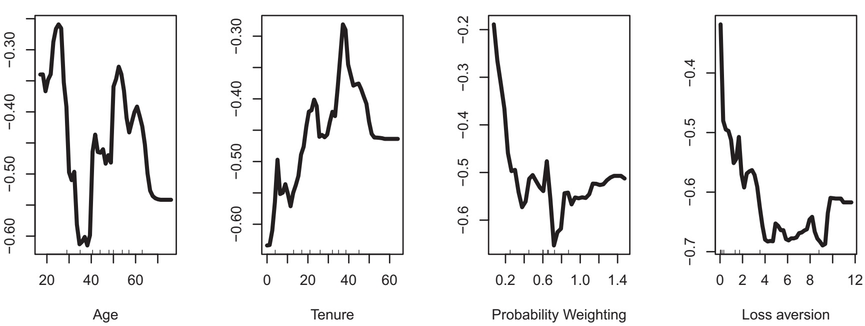

Figure 5.5 Partial dependence plots for the most important variables explaining who states they violate discarding regulations less than average

lower propensity to state that one violates less than the average, but this effect appears to be non-linear.

With respect to violating minimum size limits (Table 5.6), we find that 'Age', 'Probability weighting', 'Reason for illegal sales', and 'Reason for misreporting' are the most important variables. The 'out-of-bag' estimate of error rate is 25.3%.

Figure 5.6 shows the partial dependence plots for whether respondents state that they violate minimum size limits less than average. First, for age, the results are similar to what we found for discarding violations. Second, those who weight probabilities accurately ($\alpha = 1$) and thus follow the economic rationale of expected outcomes are least likely to report that they violate less than average. Those who either over- or underweight small probabilities are more likely to report that they violate less than average. Third, those who report 'It is unfair to others' (category 4) as a main reason for not selling fish illegally, are more likely to report that they violate size regulations less than average. Fourth, those who report that 'fear or formal punishment' (category 1)

Table 5.6 List of Selected Variables that Explain Who States that They Violate Size Regulations Same/More or Less than Average, Ordered by Decreasing Importance

	Same/ More	*Less*	*Mean Decrease Gini*
Age	2.67	−4.42	19.26
Probability weighting	5.14	−0.66	16.23
Reason for illegal sales	14.81	10.68	10.00
Reason for misreporting	9.84	9.34	8.86
Reason for not sharing info	3.31	3.60	8.60
Reason for black labor	−3.30	12.83	7.69
Reason for violating gear	4.98	2.29	6.94
Reason for violating size regulations	2.48	1.96	5.86

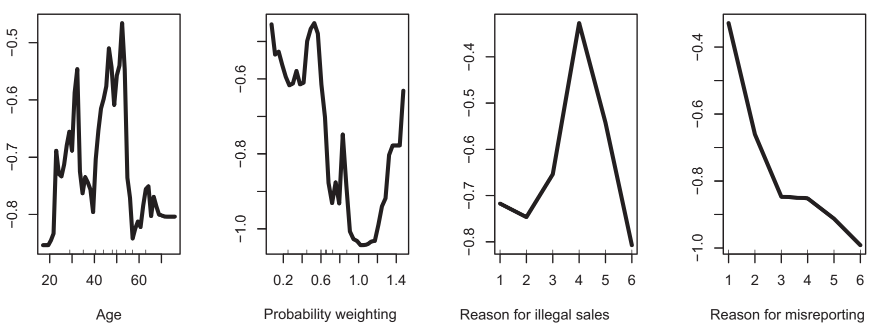

Figure 5.6 Partial dependence plots for the most important variables explaining who states they violate size regulations less than average

and 'rules must be followed' (category 2) is a main reason not to misreport are less likely to state they violate less than average.

We now turn to the question whether violations can be justified. We start by investigating which variables can explain whether discarding regulations can never be justified ($y = 1$) compared to stating that violations can be sometimes or usually be justified ($y = 0$); see Table 5.7.

The 'out-of-bag' estimate of error rate is 38.74%. We find that 'Tenure', 'Individualism', 'Altruism', and 'Income' are most important variables in explaining whether violating discarding regulations can be justified. Figure 5.7 shows partial dependence plots for the question whether violations of the discard ban can never be justified. First, like before, the jump observed in the variable 'Tenure' is due to very few individuals with tenure beyond 45 years who report that violating discarding violations can never be justified. Individuals with tenure in the industry at about 20 years are least likely to report that violating discard regulations can never be justified. Second,

Table 5.7 List of Selected Variables that Explain Who States that Violating Discard Regulations Can Never be Justified, Ordered by Decreasing Importance

	0	*1*	*Mean Decrease Gini*
Tenure	1.10	4.03	17.59
Individualism	2.65	11.72	16.54
Altruism	−2.63	3.98	14.87
Income	0.38	2.55	14.52
Years until retirement	3.04	6.85	14.30
Probability weighting	1.72	1.67	13.93
Reason for spreading wrong info	−2.07	5.93	7.24
Reason for not sharing info	0.62	3.24	6.94
Concern: Price of fish & markets	−0.42	−2.63	3.32
Vessel Owner	−1.51	−0.74	3.15

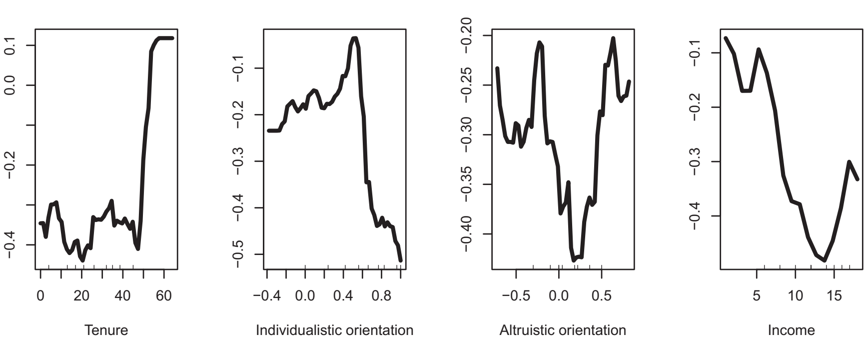

Figure 5.7 Partial dependence plots for the most important variables explaining who states that violating discard regulations can never be justified

a high individualistic orientation is correlated with a lower propensity to state that violations can "never" be justified. Third, altruism seems to have a non-linear relationship with regard to whether discarding can be justified. Finally, a higher income class, although not the highest income classes, has a negative effect on the likelihood of stating that discard regulations can never be justified. This sheds an interesting light on the correlation between compliance and economic success.

Finally, we investigate which variables are particularly important for explaining whether violating size regulations can never ($y = 1$) or sometimes or usually ($y = 0$) be justified (Table 5.8). First, we find that 'Tenure', 'Individualism', 'Altruism', and 'Income' are the most important variables. Inspecting the partial dependency plots (Figure 5.8) reveals a

Table 5.8 List of Selected Variables that Explain Who States that Violating Minimum Size Regulations Can Never ($y = 1$) or Sometimes/ Usually ($y = 0$) be Justified, Ordered by Decreasing Importance

	0	*1*	*Mean Decrease Gini*
Tenure	3.08	−1.64	12.48
Age	4.08	−0.82	12.45
Altruism	−2.05	3.41	12.28
Income	3.79	4.54	12.05
Years until retirement	3.17	1.50	11.47
Reason for illegal sales	4.98	1.51	7.59
Reason for not sharing info	1.07	0.27	6.74
Reason for misreporting	3.02	−3.00	6.41
Reason for discarding	5.89	−0.95	5.81
Education	1.81	−2.87	5.47
Reason for violating gear regulation	5.52	−0.21	5.47
Reason for violating size regulation	5.76	−2.40	5.17
Reason for black labor	2.11	−2.53	5.12
Parent Fisher	2.73	2.01	3.15
Concern: price of fish & markets	3.54	−1.63	3.06

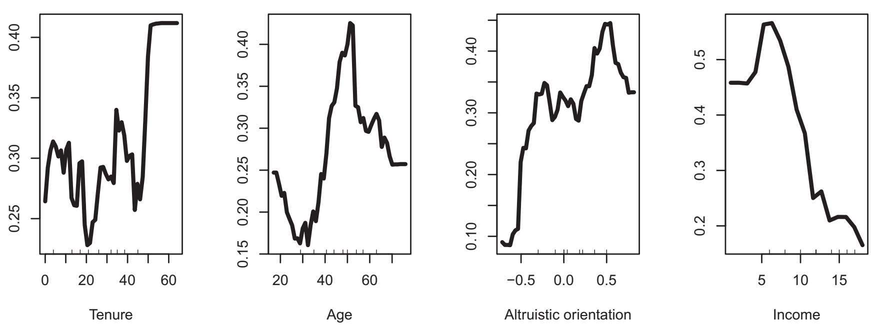

Figure 5.8 Partial dependence plots for the most important variables explaining who states that violating minimum size regulations can never be justified

non-linear pattern for tenure similar to what we observed when explaining whether discarding can be justified. Second, age shows a non-linear pattern, where individuals around 50 have the highest tendency to say that violating size regulations can never be justified. Third, we find that a more altruistic orientation correlates with saying that size violations can never be justified. Finally, like before, a higher income class has a negative effect on the likelihood of stating that violating size regulations can never be justified.

Conclusions

Globally, about 20% of all catches are still caught illegally, making lack of compliance a pressing issue. An open question is how to optimally design enforcement and monitoring schemes. Having observers and video surveillance on board of all fishing vessels is effective, but it is costly and not necessarily efficient (Diekert et al., 2021). Our study sheds light on the question to what extent formal enforcement interacts with intrinsic motivation or social norms to comply. Interestingly, the theoretical predictions are ambiguous and go in two directions. On the one hand, imperfect monitoring, capitalizing on the intrinsic motivation of most fishers, may backfire if it erodes the motivation to comply, because fishers feel that some "bad apples" get away with violating (Traxler & Winter, 2012; Richter & Grasman, 2013). In such case, strong regulation would strengthen social norms to comply. However, strong enforcement may also crowd out intrinsic motivation to comply because users feel they are mistrusted or because they feel that formal regulations have replaced social norms and they would no longer see it as their responsibility to keep an eye on what fellow fishers do (Bowles, 2008). In such case, formal regulation could crowd out social norms.

Our survey conducted among Norwegian fishers, highlight the prevalence of a strong general notion that one should follow the law as the main reason to comply with regulations. This does not mean that formal enforcement is unimportant. Rather, this conviction must be upheld, both by a functional logic, to protect fish stocks and the future development, and by a confirmation by the regulator via effective enforcement. Indeed, without such a reinforcing role of the formal management institution, the motivation of fishermen that normally comply may be irreversibly damaged.

This book chapter explores the role of economic preferences in explaining compliance attitudes and behavior. We find that compliance behavior is complex and determined by several factors simultaneously, rather than by one or some specific preferences. While economic preferences play a role, a large fraction of the variation remains specific to the individual.

Further, we find that the attitudes and motivations to comply are highly rule specific. With respect to rules that pertain most directly to the health of the resource base, such as the discard ban and minimum size regulations, the main reason for compliance was indeed the concern about the future sustainability of the fish stock. One possible reason for this result could be the specific history of Norwegian fisheries. The stock of the cornerstone species, the Northeast Atlantic cod was severely depleted throughout the 1970s and 1980s and was perceived to stand at the brink of collapse in 1989. At that time, the Norwegian authorities pulled the emergency break and closed this fishery that was traditionally open to all. Against much opposition, individual quotas were introduced as a short-term fix, and they have since become permanent. It took years to rebuild the stock, but it is today one of the most valuable whitefish fisheries in the world. The main pelagic fisheries experienced a similar story of collapse and rebuilding in the 1970s. These lessons of overcoming crisis may have had a deep impact on the fisheries discourse in Norway.

While our study sheds light on mechanisms and compliance behavior, further research is needed to understand how compliance behavior is affected by economic preferences, social norms, incentives, and wider contextual factors.

Our study has several policy implications. First, it highlights the importance of designing regulations and enforcement policies in ways that do not erode but rather maintain or strengthen intrinsic motivations to comply. This requires knowledge about fishers' compliance behavior. Furthermore, we know also from previous work that formal policies and regulations that support what fishers believe is right, are more likely to strengthen the social norms to comply (Gezelius, 2002). Hence, policy makers should provide fishers and fishing communities with platforms for knowledge sharing and participation in the policy design process. A joint understanding of what sustainable fisheries management entails and what are the main policy objectives and priorities, can strengthen the norm of sustainably harvesting the stock.

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Appendix

Table 5.A1 Summary Statistics for All Potential Explanatory Variables Used in the Machine Learning Analysis

Variable	*Mean*	*Std. Dev.*	*Min.*	*Max.*
Age	*47.23*	*12.805*	*18*	*77*
Gender (male=1)	0.98	0.125	0	1
Number of kids	2.22	1.596	0	11
Number of siblings	2.92	1.692	0	11
Parent fisher	0.55	0.498	0	1
Expect children fisher	0.17	0.38	0	1
Tenure	26.03	14.575	0	64
Vessel owner	0.65	0.478	0	1
Income	11.89	4.139	1	18
Risk tolerance	0.86	0.517	0.05	1.58
Prob weighting	0.61	0.272	0.08	1.48
Impatience	0.09	0.136	−0	0.57
Loss aversion	2.05	3.085	0.05	11.66
Altruism	0.10	0.304	−0.72	0.82
Individualism	0.59	0.360	−0.38	1
Education	3.18	0.979	1	6
Years until retirement	15.39	12.473	0	60
Concern: stock development	0.38	0.487	0	1
Concern: crew situation	0.23	0.421	0	1
Concern: cost development	0.41	0.493	0	1
Concern: fish price & market	0.62	0.487	0	1
Concern: political uncertainty	0.28	0.448	0	1
Concern: regulation complexity	0.23	0.424	0	1
Concern: nature & Climate	0.10	0.299	0	1
Concern: quota policy	0.44	0.498	0	1
Concern: next Generation	0.15	0.362	0	1
Pelagic	0.17	0.376	0	1
North	0.49	0.501	0	1

Table 5.A2 Four Pairwise Lottery Choices (in Norwegian Krones)

Experiment 1

	Lottery A		*Lottery B*		*Expected payoff diff.*
Situations	*High (Prob=0.3)*	*Low (Prob=0.7)*	*High (Prob=0.1)*	*Low (Prob=0.9)*	*(A–B)*
1	83	21	141	10	16.5
2	83	21	155	10	15.1
3	83	21	172	10	13.4
4	83	21	193	10	11.3
5	83	21	220	10	8.6
6	83	21	259	10	4.7
7	83	21	311	10	−0.5
8	83	21	383	10	−7.7
9	83	21	456	10	−15
10	83	21	621	10	−31.5
11	83	21	828	10	−52.2
12	83	21	1243	10	−93.7
13	83	21	2071	10	−176.5
14	83	21	3521	10	−321.5

Experiment 2

Situations	*Lottery A* *High (Prob=0.9)*	*Low (Prob=0.1)*	*Lottery B* *High (Prob=0.7)*	*Low (Prob=0.3)*	*Expected payoff diff.* *(A–B)*
1	83	62	112	10	−0.5
2	83	62	116	10	−3.3
3	83	62	120	10	−6.1
4	83	62	124	10	−8.9
5	83	62	128	10	−11.7
6	83	62	135	10	−16.6
7	83	62	141	10	−20.8
8	83	62	149	10	−26.4
9	83	62	159	10	−33.4
10	83	62	172	10	−42.5
11	83	62	186	10	−52.3
12	83	62	207	10	−67.0
13	83	62	228	10	−81.7
14	83	62	269	10	−110.4

Experiment 3

Situations	*Lottery A* *High (Prob=0.5)*	*Low (Prob=0.5)*	*Lottery B* *High (Prob=0.5)*	*Low (Prob=0.5)*	*Expected payoff diff.* *(A–B)*
1	252	−40	302	−211	60.5
2	40	−40	302	−211	−45.5
3	10	−40	302	−211	−60.5
4	10	−40	302	−161	−85.5
5	10	−81	302	−161	−106
6	10	−81	302	−141	−116
7	10	−81	302	−111	−131

Table 5.A3 Choices in the Social Preference Experiment

Situation	*Choice A*		*Choice B*	
	You	*Other*	*You*	*Other*
1	+230	−100	+180	−180
2	+100	+230	+180	+180
3	+250	+0	+230	−100
4	−180	+180	−100	+230
5	+180	+180	+230	+100
6	−250	+0	−230	+100
7	−100	−230	−180	−180
8	+0	+250	+100	+230
9	+100	−230	+0	−250
10	−230	−100	−250	+0
11	−180	−180	−230	−100
12	+230	+100	+250	+0
13	+180	−180	+100	−230
14	−230	+100	−180	+180
15	−100	+230	+0	+250
16	+0	−250	−100	−230