Econometric Ways to Estimate the Age and Price of Abalone

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Abstract: Abalone is a rich nutritious food resource in the many parts of the world. The economic value of abalone is positively correlated with its age. However, determining the age of abalone is a cumbersome as well as expensive process which increases the cost and limits its popularity. This article proposes very simple ways to determine the age of abalones using econometric methods to reduce the costs of producers as well as consumers.

Key Words: Ordinary Least Square Model, Ordered Probit Model.

Introduction: Abalone is an excellent source of iron and pantothenic acid, is a nutritious food resource and farming in many parts of the world. 100 grams of abalone yields more than 20% recommended daily intake of these nutrients. Abalones have long been a valuable food source for humans in every area of the world where a species is abundant. The meat of this mollusc is considered a delicacy in certain parts of Latin America (especially Chile), France, New Zealand, Southeast Asia, and East Asia (especially in China, Vietnam, Japan, and Korea). Abalone pearl jewelry is very popular in New Zealand and Australia, in no minor part due to the marketing and farming efforts of pearl companies. Unlike the Oriental Natural, the Akoya pearl, and the South Sea and Tahitian cultured pearls, abalone pearls are not primarily judged by their roundness. The inner shell of the abalone is an iridescent swirl of intense colors, ranging from deep cobalt blue and peacock green to purples, creams and pinks. Therefore, each pearl, natural or cultured, will have its own unique collage of colors. The shells of abalone are occasionally used in New Age smudging ceremonies to catch falling ash. They have also been used as incense burners. In the same way as shark fin soup or bird's nest soup, abalone is considered a luxury item, and is

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traditionally reserved for special occasions such as weddings and other celebrations. Farming of abalone began in the late 1950s and early 1960s in Japan and China. Since the mid-1990s, there have been many increasingly successful endeavors to commercially farm abalone for the purpose of consumption. Overfishing and poaching have reduced wild populations to such an extent that farmed abalone now supplies most of the abalone meat consumed. The principal abalone farming regions are China, Taiwan, Japan, and Korea. Abalone is also farmed in Australia, Canada, Chile, France, Iceland, Ireland, Mexico, Namibia, New Zealand, South Africa, Thailand, and the United States. The economic value of abalone is positively correlated with its age. Therefore, to detect the age of abalone accurately is important for both farmers and customers to determine its price. Determining the actual age of an abalone is a bit like estimating the age of a tree. Rings are formed in the shell of the abalone as it grows, usually at the rate of one ring per year. Getting access to the rings of an abalone involves cutting the shell. After polishing and staining, a lab technician examines a shell sample under a microscope and counts the rings. Because some rings are hard to make out using this method, the researchers believed adding 1.5 to the ring count is a reasonable approximation of the abalones age. This complex method increases the cost and limits its popularity. Hence, researchers are interested in relating abalone age to variables like length, height and weight of the animal. If a reasonably accurate model could be found to predict the age of abalone, then the farmers would minimize the cost and customers would get the expected goods. Our target is to find out the best indicators to forecast the rings, then the age of abalones.

Literature Review: Researchers are making new ideas to determine the age of abalone using different techniques. For example, marine biologists are using the laboratory experiment to determine the age of abalone, machine learning scientists are using classification technique using physical characteristics of abalone to determine the age, econometricians and statisticians are also using physical characteristics of abalone to determine the age using different kinds of regression as well as clustering, and many other people are using different methods to detect the age of abalone. Marine biologists Takami, H. et al. [9] developed an age determination method for larval and newly metamorphosed post-larval abalone Haliotis discus hannai in a laboratory experiment and determined the age of field caught individuals. Day, R. W. et al. [4] developed a method where they assessed the potential of five fluorochromes in marking shells of the abalone

Haliotis rubra, using an immersion technique. Such marks are required to 'time stamp' the shells and thus determine whether shell layers are deposited regularly enough to be used to age abalone. Troynikov, V. S. et al. [10] describe that abalone growth is notoriously variable, changing dramatically between seasons and sites. They also mention that juvenile growth does not fit the commonly used von Bertalanffy model and they present a modified deterministic Gompertz model for tagging data and three stochastic versions in which asymptotic length is a random parameter. They use Kullback's informative mean to discriminate between models with respect to the fit to data. Siddeek, M. S. M., and Johnson, D. W. [8] describe that length-frequency data for Omani abalone (Haliotis mariae) from two areas (Sadh and Hadbin) of the Dhofar coast of the Sultanate of Oman were used to fit von Bertalanffy growth curves by ELEFAN, MULTIFAN and Non-Linear Least Square Fitting methods. The first two methods were directly applied to length-frequencies whereas the last method was used on the length modes determined by the MIX method. The growth parameter values by sex and area were not significantly different. Al-Daoud, E. [1] uses neural network technique to classify the number of rings using physical characteristics. Using the von Bertalanffy growth equation Bretos, M. [2] proposes a method to determine the age of abalone. Gurney, L. J., et al. [6] describe the stable oxygen isotopes procedure to determine the blacklip abalone *Haliotis rubra* in south-east Tasmania. However, Naylor, et al. [7] find that the method, variations in the ratios of carbon isotopes, showed no consistent patterns and unlike some mosllusc, do not appear to be useful predictors of reproductive status at length.

Description of the Data: In this article, the data set Abalone, a cross sectional data, is obtained from UCI Machine Learning Repository developed by Dua, D. and Karra Taniskidou, E. [5]. The data set contains physical measurements of 4177 abalones recorded in December 1995 by Marine Research Laboratories Taroona, Department of Primary Industry and Fisheries, Tasmania, Australia. There are nine variables, namely, Sex, Length, Diameter, Height, Whole weight, Shucked weight, Viscera weight, Shell weight and Rings. All variables are quantitative but Sex. The variable Rings is somehow related to the age of an abalone, as age equals to number of rings plus 1.5. This data set was used in many facets of research. For example, Waugh, S. [11] used this data set in his PhD thesis on titled "Extending and benchmarking

Cascade-Correlation", and Clark, D. et al. [3] used this data set to write an article on "A Quantitative Comparison of Dystal and Backpropagation", which they submitted to the

Table 1. Raw Data Series

Variable	Variable Name	Data Type	Meas.	Description
sex	Sex	Nominal		M, F, and I (infant)
length	Length	Continuous	Mm	Longest shell measurement
diameter	Diameter	Continuous	Mm	Perpendicular to length
height	Height	Continuous	Mm	with meat in shell
wweight	Whole weight	Continuous	Grams	Whole abalone
sweight	Shucked weight	Continuous	Grams	Weight of meat
vweight	Viscera weight	Continuous	Grams	Gut weight(after bleeding)
shweight	Shell weight	Continuous	Grams	After being dried
rings	Rings	Integer		+1.5 gives the age in years

Table 2. Summary of the Quantitative Variables

Variable	Obs	Mean	St.dev.	Min	Max
length	4,177	0.524	0.120	0.075	0.815
diameter	4,177	0.408	0.099	0.055	0.650
height	4,177	0.140	0.042	0.000	1.130
wweight	4,177	0.829	0.490	0.002	2.826
sweight	4,177	0.359	0.222	0.001	1.488
vweight	4,177	0.181	0.110	0.001	0.760
shweight	4,177	0.239	0.139	0.002	1.005
rings	4,177	9.934	3.224	1.000	29.000

Australian Conference on Neural Networks. Table 1 describes the tabular form of the data. If we look at the summary (Table 2) of the quantitative variables we can see that the maximum number of rings is 29 and minimum 1, which means some of the abalones are very young and some are very old. We can also see that the minimum height is 0 which does not make any sense. We have 2 observations with zero height. May be these are typo. Class description (Table 3) indicates that very few observations are greater than 21, and class 1 has one observation and class 2 has 1 observation also. It looks most of the observations are between 5 and 15. From the summary (Table 4) of the categorical variable sex we can see that 31.29% are female, 32.13% are infant, and 36.58% are male. Notice that in all variables there is no missing value. Now if we look at the histogram (Figure 1) of the response variable rings then we can see that the distribution does not look normal.

Table 3. Class Description of Data: A=class, B=number of observations

A	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	29
B	1	1	15	57	115	259	391	568	689	634	487	267	203	126	105	67	58	42	32	26	14	6	9	2	1	1	2	1

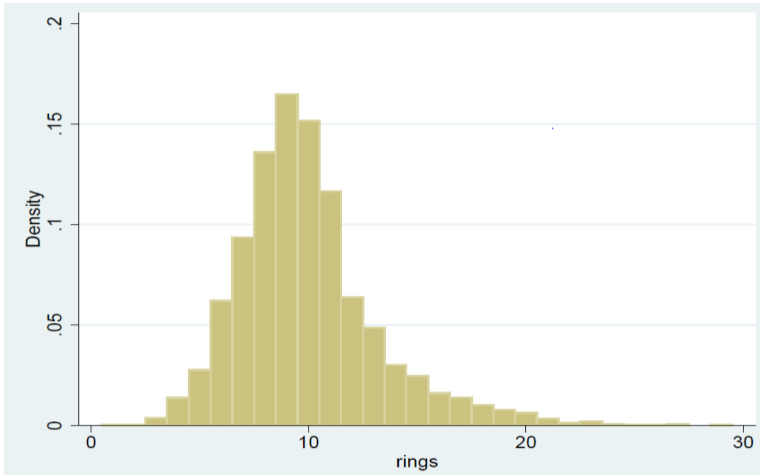
Table 4. Summary of the Categorical Variable sex

sex	Freq.	Percent	Cum
F	1,307	31.99	31.29
I	1,342	32.13	63.42
M	1,528	36.58	100.00
	4,177	100.00	

Model Selection: Here we will try to predict the number of rings using two types of models, least square estimation model and ordered probit model.

Least Square Estimation Model: Our target is to predict the number of rings on the basis of other observations. To do this we should visualize the relations of the other variables with the variable rings. One way is to see that using matrix graph (Figure 2), which shows scatter diagrams among the variables. From the matrix diagram we can see how the objective variable ring is related to the other variables. We can see there are two outliers in the scatter diagram of rings and height, and some other kind of outliers are visible among other variables. It looks rings is linearly related with length , height, and diameter. The variables wweight, sweight, vweight,

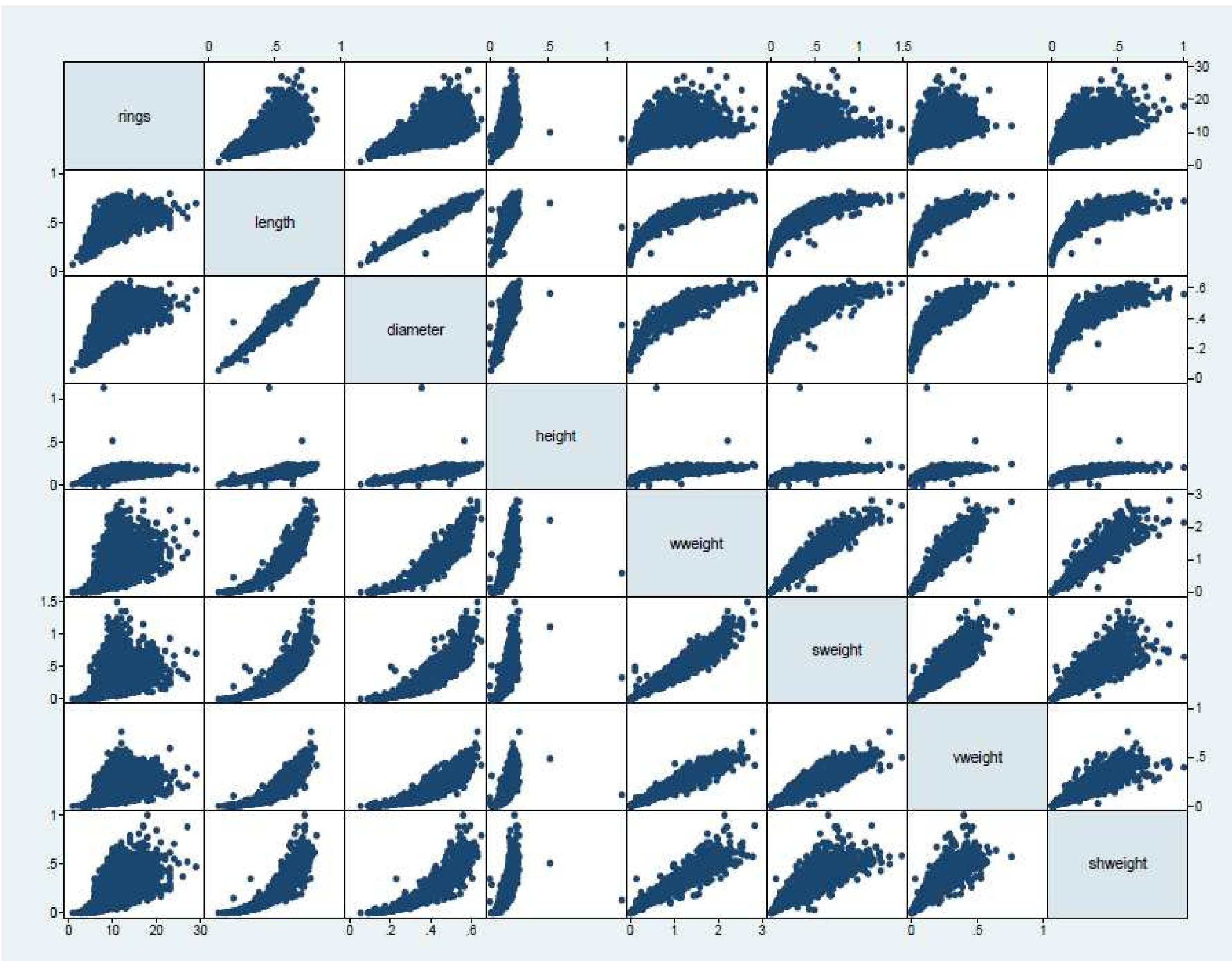
Figure 1. Histogram of the dependent variable rings



and shweight have somewhat a logarithmic relations with ring. In this article we want to develop a model which will help the firms and consumers to identify the age of the abalones in a very simple way. Because of these, in this study we will ignore the variables sweight, vweight, and shweight since the measurement of this variables are not quite simple. To predict the number of rings we will try to use the variables length, diameter, height, and wweight, because these are very easy to measure. We did not discuss about the categorical variable sex yet. Might be sex is an important variable to determine the number of rings. We examine this variable also using three different matrix diagrams shown in Figure 3 since it has three categories female, infant, and male. From the matrix diagrams of three categories we can see that there is a outlier in the scatter diagram of rings and height in category female, one outlier in the scatter diagram of rings and height in category male. We can also see that the relations of rings with the variables length, diameter, and height looks linear in all categories but in different degrees, however, somewhat logarithmic with wweight in all categories in different degrees. Therefore, it looks these categories have different effect on rings.

Now we will examine how the variables are correlated to each other. In other words we will see the covariance matrix. From the covariance matrix (Table 5, numbers without parentheses) we can see that rings is positively correlated with other variables which is expected, however, somewhat in low degrees compare to the relation among the explanatory variables. If we transform the variables wweight to ln(wweight) then may be we will have stronger correlation of rings with other variables. We can see that the correlation (Table 5, numbers in the brackets) changes a little bit but not much, however the other variables are highly positively correlated among themselves.

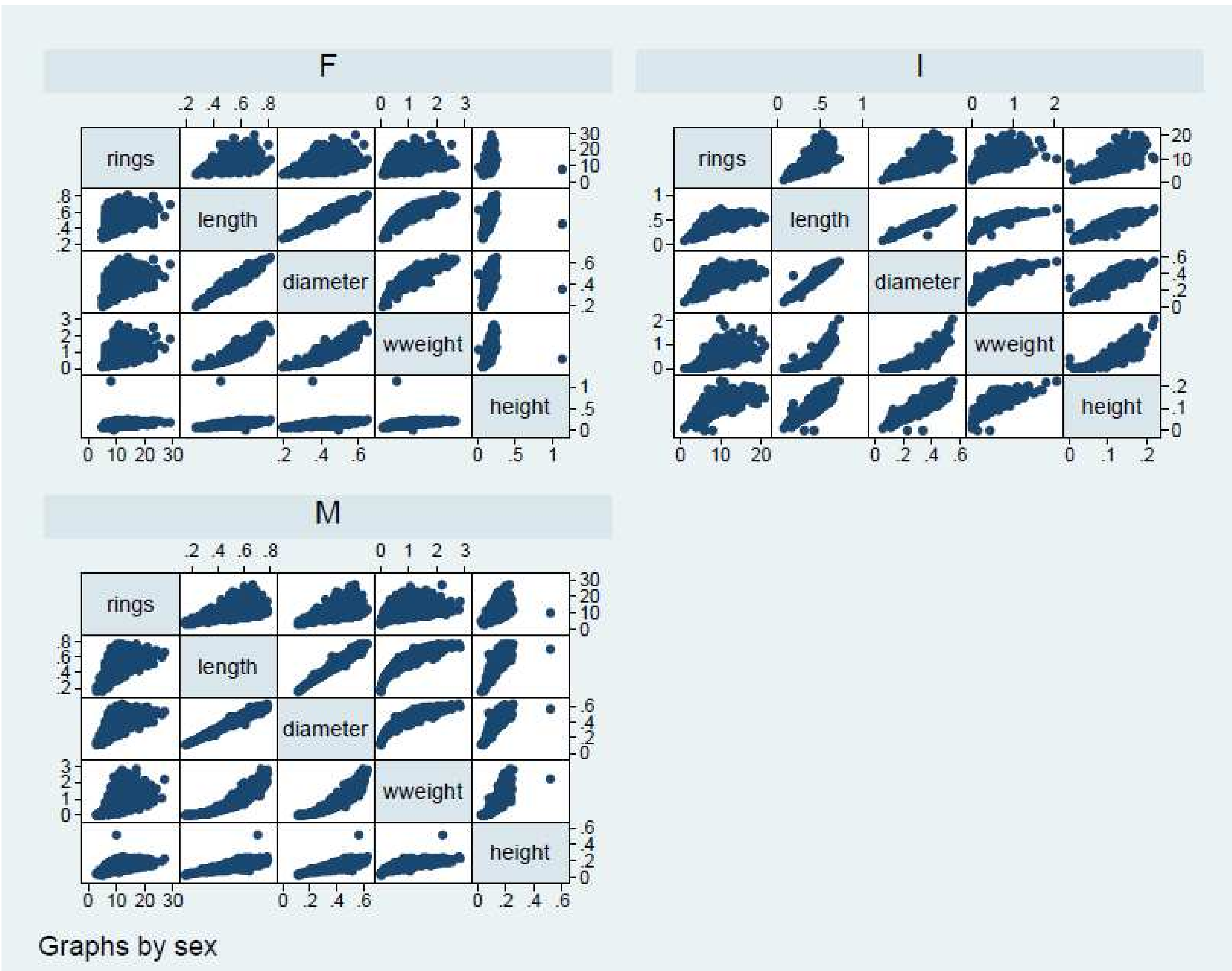
Figure 2. Matrix diagram of the variables



Performing ordinary least square regression (OLS) for rings on ln(weight), height, diameter, length, category1 (female), and category3 (male) considering category2 (infant) as base group we get the estimates in column 1, Table 6 which indicate that all estimates are statistically other than zero at 1% level of significance using individual t-test. The R-sq=0.3822 indicates that only

38.22% of the variation in rings is explained by this regression model. From the result we can see that the estimate of the coefficient of length is negative which is unexpected. We suspect that we are getting this unexpected result because of high correlation among explanatory variables.

Figure 3. Matrix diagram of on the basis of sex



Since the explanatory variables are highly correlated with each other, we highly suspect that there is multicollinearity problem. If we test the multicollinearity of the explanatory variables length, diameter, height, and ln(wweight) using the above regression then we get the results in row 1, Table 7. The results show that the VIF of all variables are greater than 5 except the category variables, and height. This test indicates that there is multicollinearity problem. To get rid of this problem we try another OLS regression where we regress rings on ln(wweight), diameter, height, category1, and category3. Doing so, we have the results in the second column of the Table 6. From the regression results we can see that estimates of all coefficients are statistically other than zero at 1% level of significance except the estimate of the coefficient of diameter using individual t-test. Statistically the estimate of the coefficient of diameter is not other than zero. And the R-sq=37.19, which indicates that 37.19% of the variation of rings is explained by this regression model which is little bit smaller than the previous regression. Since statistically the estimates of the coefficient of diameter is not other than zero, we try with another OLS regression where we regress rings on ln(wweight), height, category1, and category3. Doing so, we get the result in column 3, Table 6. The regression tells that all estimates of the coefficients are statistically other than zero at 1% level of significance using individual t-test. 37.19% of the variation of rings is explained by this regression model. Now if we perform the VIF test to identify the multicollinearity problem then we get the following result in row 2, Table 7. The VIF result indicates that there is no strong multicollinearity between ln(wweight) and

Table 5. Covariance matrices

	rings	wweight [ln(wweight)]	height	diameter	length
rings	1.00				
wweight [ln(wweight)]	0.54 [0.58]	1.00			
height	0.56	0.82 [0.83]	1.00		
diameter	0.57	0.93 [0.96]	0.83	1.00	
length	0.56	0.93 [0.97]	0.83	0.99	1.00

height. Figure 4 represents the histogram of the residuals of the OLS regression (column 3, Table 6) . This histogram is positively skewed which indicates that the regression model violates the normality assumption of the residuals. However, it doesn't look highly skewed. Now if we do White's test for heteroskedasticity of the last regression (column 3, Table 6) then we get p-value 0.00 which indicates that there is heteroskedasticity problem. To get rid of this problem we will use robust estimation. Doing so, we have the OLS regression result in column 4, Table 6. We can see that all of the robust standard errors are greater than those in the previous OLS regression (column 3, Table 6) except the standard error for the estimates of category3. These results are telling us that all of the estimates are statistically other than zero at 1% level of significance except the estimates of the coefficient of height using individual t-test. The estimate of the coefficient of height is not statistically other than zero at 5% level of significance. However, it is statistically other than zero at 6% level of significance. The 95% confidence interval, (-0.15, 32.26), of the estimate of the coefficient of height is really wide which indicates that the corresponding point estimate is not so reliable. We have two zero observations of the variable height. Ignoring those two zero observations if we perform OLS (robust) regression using the

Table 6. Regression results from different specification where rings is dependent variable

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	10.02***	7.23***	7.59***	7.59***	7.57***	4.05***	8.09***
	(0.77)	(0.70)	(0.28)	(1.26)	(1.28)	(0.50)	(1.39)
lnwweight	1.76****	1.18***	1.27***	1.27***	1.27***	0.49***	1.51***
	(0.19)	(0.18)	(0.90)	(0.33)	(0.34)	(0.12)	(0.37)
height	15.75***	15.85***	16.06***	16.06*	16.17*	45.12***	17.94**
	(1.74)	(1.75)	(1.71)	(8.26)	(8.39)	(3.81)	(8.81)
category1	1.00***	1.07***	1.07***	1.07***	1.08***	0.98***	
	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.11)	
category3	0.84***	0.90***	0.90***	0.90***	0.90***	0.82***	
	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.10)	
diameter	17.99***	0.85*					
	(2.56)	(1.53)					
length	-18.06***						
	(2.17)						
sqheight						-38.14***	
						(3.01)	
R-sq	0.38	0.37	0.37	0.37	0.37	0.39	0.36
N	4,177	4,177	4,177	4,177	4,175	4,177	4,177

*p<0.10, **p<0.05, ***p<0.01. Standard Errors in parentheses.

same explanatory variables then we get result in column 5, Table 6. This result indicates that there is no significant difference between the last two regressions since the estimates of the coefficients and the standard errors are almost identical. So it doesn't make any difference whether we use the full data set or ignore two zero observations from the variable height. Now if we summarize the predicted values using the last model (column 5, Table 6) then we get the variable rings covers from -0.15 to 26.14. Actually we have only one negative predicted value which is unexpected. Other than that our predicted values are covering almost the whole range of the variable rings.

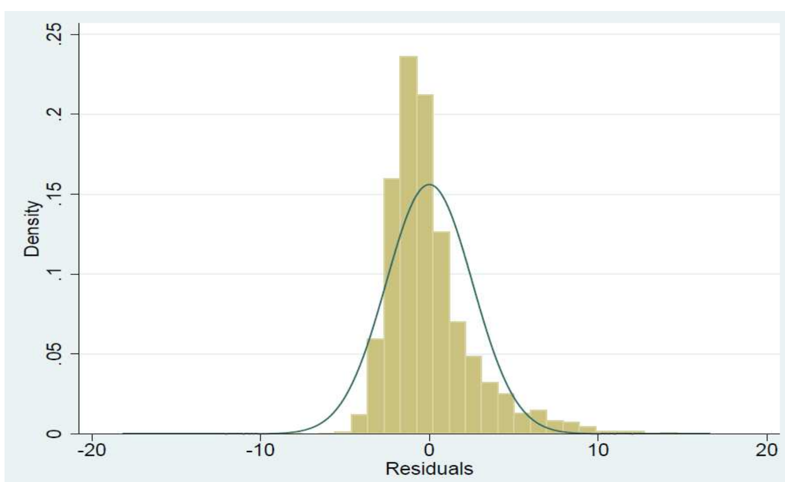
Now let's try with adding the variable $height^2$ in the model. If we regress (OLS with robust standard error) rings on ln(wweight), height, $height^2$, category1, and category3 we get the results

Table 7. VIF test results for the regression

	length	diameter	lnwweight	height	category1	category3
(1)	44.01	41.86	16.70	3.43	1.92	1.83
(2)			3.51	3.28	1.90	1.82

in column 6, Table 6. All estimates are statistically significant at 1% level of significance using

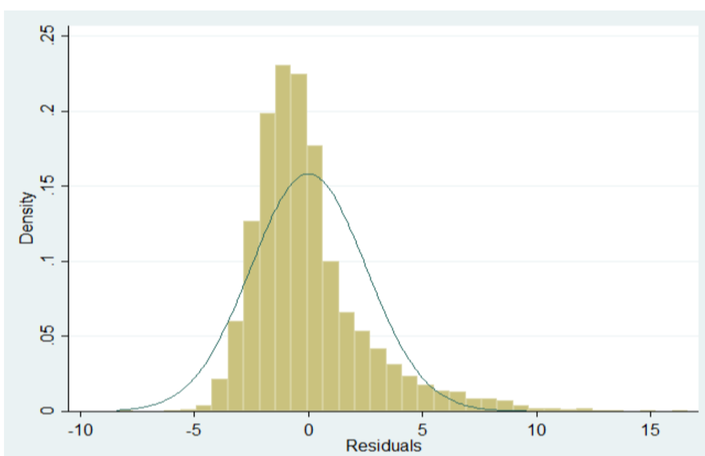
Figure 4. Histogram of the residuals of the OLS model (column 3, Table 6)



individual t-test. So the term $height^2$ has an impact on rings. However, the 95% confidence interval for the variable height [(37.66, 52.58)], and $height^2$ [(-44.03,-32.244)] look somewhat wide which indicate that corresponding point estimates are kind of week. Let's look at the predicted values, and histogram (Figure 5) of the residuals. Now if we summarize the predicted values using the above model then we get the variable rings covers from 1.44 to 18.44. We learn from the classification of the variables, in Table 3, that most of the observations of the variable rings are between 3 and 15. And we have total two observations in class 1 and 2, and very few observations are greater than 21 and less than 3. So this model is considerable. The histogram of the residuals is still positively skewed but better than the previous one. Therefore this model looks better than the previous model.

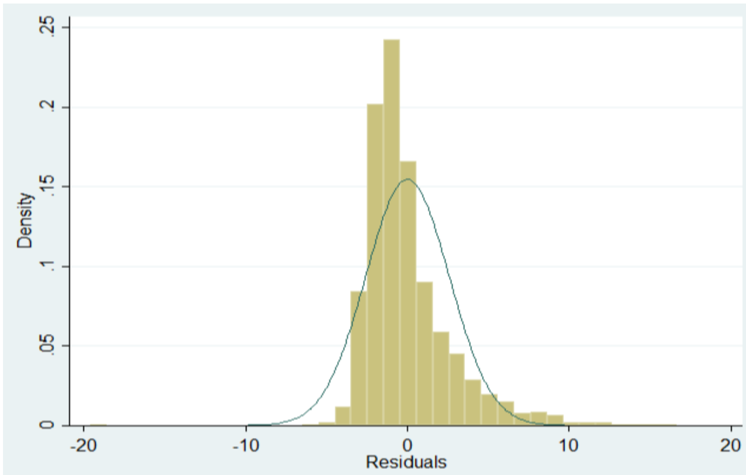
Now if we want to make it simpler even the simplest to predict the age of the abalone for the farmers and consumers then we can ignore the variable sex since determining sex is not so simple. Ignoring the variable sex if we perform OLS (robust) regression for rings on ln(wweight) and height then we get the estimates in column 7, Table 6. We can see that all estimates are statistically other than zero at 5% level of significance using individual t-test. However, the 95% confidence interval (0.66, 35.23) for the variable height is really wide which indicates the point estimate of the coefficient of height is not satisfactory. Here the range of the predicted values of rings using the model covers from -1.1 to 27.58. Actually here we have only

Figure 5. Histogram of the residuals of the OLS model (column 6, Table 6)



one negative predicted value which is unexpected. However, these predicted values cover almost the whole range of the predictor variable rings. This model will reflect very good prediction if someone wants to ignore the variable sex. From the histogram (Figure 6) of the residuals of the last model we can see that it is positively skewed. However, it looks more skewed than the previous two histograms.

Figure 6. Histogram of the residuals of the OLS model (column 7, Table 6)



Actually we tried with many different combinations of the explanatory variables and their higher orders and logarithmic transformations to predict the variable rings. In all models we get heteroskedasticity problem. For this reason we always estimate robust standard errors. Now the question is: can we tolerate this skewness for the sake of our analysis?

Therefore on the basis of above analysis we would like to propose the least square regression model (column 6, Table 6)

$$rings=4.05+0.49ln(wweight)+45.12height-38.14height^2+0.98category1+0.82category3 \quad \text{(M1)}$$

with robust standard error considering category2 (infant) as base group to predict the number of rings, and then the age of abalone. The intercept 4.05 has no good explanation because all explanatory variables will never be zero. The coefficient of ln(wweight) is telling us if whole weight (wweight) increases by 1% (unit of wweight is grams) then the number of rings increases by 0.49% holding all others constant. The coefficient of height is telling us that for each additional mm height the number of rings will increase by 45.12-76.28*height* holding all other constant[3]. The coefficient of the category1 (female) is telling us that female has 0.98 rings more

[3] All observations are less than 0.5915 mm except one observation. So the variable rings increases with respect to the explanatory variable height with a decreasing rate holding all other variables constant.

than the infant(category2) holding all other constant. The coefficient of the category3 (male) is telling us that male has 0.82 rings more than the infant (category2) holding all other constant.
If somebody wants to use the most simplest model ignoring the categorical variable, sex, then we want to propose the following least square regression model (column 7, Table 6) with robust standard error to predict the number of rings where ln(wweight) and height are the explanatory variables, and then the age of abalone. The proposed model (estimated) is

$$rings=8.09+1.51lnwweight+17.94height \quad \text{(M2)}$$

Ordered Probit Model: We have proposed an ordinary least square model (M2) with robust standard errors ignoring the categorical variable sex where the response variable is rings and the explanatory variables are ln(wweight), height. However, in that model we can see that the confidence intervals[4] of the estimated coefficients are not quite reliable. Now we would like to develop a very simple ordered probit model ignoring the categorical variable sex where the ordered variable is assigned as class=1 if rings is less than 9, class=2 if rings is greater than or equal to 9 and less than 18, and class=3 if rings is greater than 18. So we divided the variable rings in three classes with ordered values. For simplicity of the farmers and consumers we will make this model very simple by not using the variable sex. Since identifying the gender is not

Table 8: Ordered probit model estimates

	length	diameter	Height	lnwweight	/cut1	/cut2	N
(1)	-5.80***	7.44***	4.22***	1.09***	-0.41	2.56	4,177
	(1.15)	(1.38)	(0.80)	(0.14)	(0.51)	(0.52)	
(2)		2.45**	4.42***	0.82***	0.74	3.69	4,177
		(0.96)	(0.80)	(0.13)	(0.45)	(0.46)	

$^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$. Standard Errors in parentheses.

trivial and if we observe the data then we can see that the variable sex is kind of overlapped. It is really hard to tell how many rings are required to be an infant for an abalone. Now using the above class variable we have the following estimates where the response variable is rings, and

[4] Confidence interval of height and lnwweight are (0.66, 35.23) and (0.79, 2.23)

the explanatory variables are length, diameter, height, and ln(wweight). From the estimates in row 1, Table 8, we can see that the variable length has a negative effect on rings which is somehow questionable even though all estimates are significant at 1% level of significance. So we would like to estimate another ordered probit model where we will not include the variable length. Doing so, we get The estimates in row 2, Table 8, indicate that the variables diameters, height, and ln(wweight) has positive effect on ring and all estimates are significant at 1% level of the significance. So we would like to propose the ordered probit model(row 2, Table 8) to predict the variable rings.

Model Experiment: To do an experiment of the above proposed models (M1, M2 and Ordered probit model) we randomly select 6 observations from 3 classes. We select 2 observations from each class. Table 9 represents the experimental results. Since rings is an integer variable, we use the nearest integer values of the predicted values of rings. From the Table 9 we can see that the rings are estimated by OLS models, and classified by ordered probit model very well when the number of rings are between 3 to 14, however, when the number of rings are larger neither OLS models nor ordered probit model works well. We can also see that the estimated M1 and M2 are comparable. Using the above results we can predict the age of abalone. As we discussed before the age of abalone is measured by the number of rings plus 1.5. From our experimental results, 10 rings were observed in the observation number1902. So the actual age of this abalone is 10+1.5=11.5 years. Using our first proposed estimated model, model 1, we predict that this

Table 9: Actual and predicted number of rings using different models

Obs#	actual # of rings	M1	M2	ordered-probit
306	4	5	4	1
1902	10	10	11	2
2202	25	13	12	2
2356	13	10	10	2
2363	18	13	12	2
3720	7	7	8	1

abalone has 10 rings, hence the predicted age is 10+1.5=11.5 years, which is predicted exactly the same as the actual age, however, by the second estimated model, model 2, the age is predicted 12.5 years. Ordered probit model has classified this abalone in the class 2, which is the actual class of this abalone. On the other hand from the observation number 2202 we can see that the actual number of rings is 25, however, it was predicted by the OLS models as 13 by the first model, 12 by the second model, and classified as class 2 by the ordered probit model. For this sample the prediction is far away from the actual value. Similarly we can predict the age of the all observed abalones from the Table 9. Actually our proposed models work fine if the rings of the abalone is between 3 to 14. It seems for larger number of rings the proposed models are not working well.

Conclusion: The economic value of abalone is positively correlated with its age. Estimating the age of abalone accurately is important for both farmers and customers to determine its price. On the basis of this analysis it seems the proposed OLS regression models, M1, M2, and ordered probit model (row 2, Table 8) work well to predict or classify the variable rings while number of rings lies between 3 to 14. We have proposed the first model (M1) if somebody wants to take care of the variable sex, otherwise second model (M2) or ordered probit model. However, in this analysis ordered probit model is not so accurate since we have only three classes. On the basis of the shape of the histogram of the residuals, M1 where the categorical variable sex is included work better than the M2, where the categorical variable sex is not included. However, these two models are comparable on the basis of our experimental results. This analysis indicates that we do not need to count the number of rings using microscopic experiment. In other words, we do not need any laboratory experiment to predict the age of abalones. We can predict the age and price of abalone using the very simple physical characteristics like weight, height, diameter, and length.

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