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Discussion on Whether the Wildlife Trade Should be Banned for a Long Time

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Abstract

Wildlife markets are the suspected source of the current outbreak and the 2002 SARS outbreak, and the consumption of wild meat is thought to be the source of the Ebola virus in Africa. After the new coronavirus outbreak, the trade regarding wildlife markets was once again thrust into the limelight. We need to analyze how trade in wildlife products should be regulated in the context of relevant realities and specific data to answer the six questions in this case.

Keywords

Data Processing; Animal Trade; Pearson Correlation; Multiple Regression Analysis.

1. Introduction

In order to indicate the origin of the Should the wildlife trade be banned for a long time problem, the following background is worth mentioning.

1.1. Proposal for the Wilderness Ban

In 2020, an outbreak of a new coronavirus was believed to have originated in a wildlife market in Wuhan. Wilt Lipkin, director of the World Health Organization (WHO) Joint Diagnostic Centre for Zoonotic and Emerging Infectious Diseases and a leading epidemiologist, came to Wuhan to learn about the outbreak and made two recommendations: 1. Please be sure to close the wildlife trading market permanently and effectively regulate the wildlife, livestock, and slaughter industries. If the wildlife trade is not closed, in 10 years, there may be new outbreaks of disease. 2. Establish a global epidemic prevention system, with each member country sharing data to face humans' complex public health and health problems. On February 24, 2020, China's top legislature officially announced an immediate ban on wildlife trade and consumption. Eliminate the indiscriminate consumption of wildlife.

1.2. The Danger of Wildlife Trade

Caroline Fukushima, a researcher at the Finnish Museum of Natural History (University of Helsinki), has said, "Legal trade does not necessarily mean 'sustainable production or trade'. Illegal or unsustainable wildlife trade (IUWT) is one of the top five drivers of biodiversity loss and extinction on a global scale." The non-compliant wildlife trade is a catalyst for the dramatic decline of wildlife and endangered species and can be extremely harmful to the balance and stable development of ecosystems and the biosphere. Illegal hunting, trading, and indiscriminate consumption of wild animals not only directly cause the reduction of individual animals, the imbalance of population structure, and the increase of illegal processing and utilization activities, but also expand the risk of invasion of exotic species and steeply increase the possibility of outbreaks and epidemics of zoonotic infectious diseases, and the normal life of humans will be seriously violated and their own health threatened[1].

Wildlife trade has many negative impacts, the most important of which are: population decline and extinction, the introduction of invasive species, and the spread of new diseases to humans.

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1.3. Sustainable Trade in Wildlife Products

For their part, some researchers say that sustainable trade in some animals is possible and beneficial to those who depend on wild animals for their livelihoods. The non-profit Entrepreneurs and Ecology Society in Beijing estimates that a ban on wild meat could cost China's economy 50 billion yuan ($7.1 billion) and put 1 million people out of work. The farming and trade of wild animals are of interest to many consumers and producers, especially the livelihoods of farmers. Many farmers have taken out loans to start wildlife farming with the support of government incentives, and the policy of banning wildlife consumption will cause significant economic losses to them[2].

2. Assumptions

- Assume that illegal and legal trade coexist in the animal trade.
- Assume that the animal trade must carry viruses.
- Assume that most of the animals in the animal trade process are wild.
- Assume that the main raw material for fur products is wild animal hides and skins.
- Assume that the animal trade process is not affected by force majeure factors such as epidemics and weather.

3. Notations

Table 1. Notations

$\bar{X}, \bar{Y}$	sample mean
Cov (X, Y)	covariance (math.)
r_{XY}	Pearson Correlation
S_X	sample standard deviation of X
H_0	original assumption
H_1	alternative assumption
t	total quantity
y	explained variable
x_i	explanatory variable
β_i	unknown parameter
Y_i	observed value
μ	random error term
$\hat{\beta}_i$	parameter estimation
$\hat{Y}_i$	regression or fitted value of Y_i
e_i	residual

4. Data Processing and Analysis

4.1. Problem 1 Solution

4.1.1. Comparison of Trade in Various Wildlife Groups

Using the CITES trade database, we extracted mammal group trade data from 1990 to 2021. To find out more intuitively which wildlife groups were traded the most, we used Matlab to write data processing code to count the number of trades according to the group classification, arranged in order from largest to smallest. And we used excel to draw a cluster bar graph to show the difference in trade volume between the 10 wildlife groups with the highest trade volume. As shown in Figure 1.

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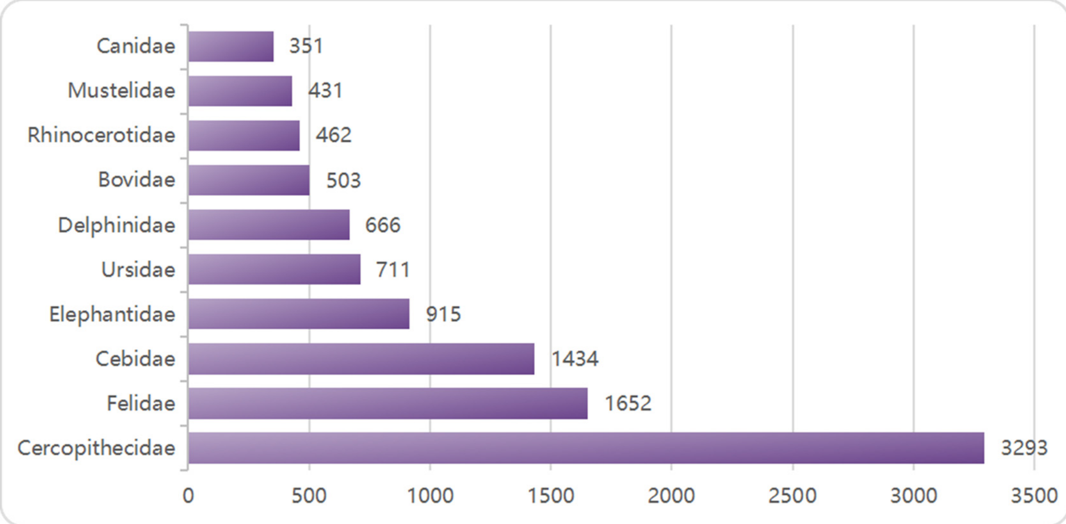

Figure 1. Comparison of trade volume by wildlife groups 1990-2021

The data and images show that the most frequently traded wildlife group in the last 30 years is the Cercopithecidae, with a total trade of 3,293 and far ahead of the Felidae in second place, with a total trade of 1,652, nearly one-half that of the Cercopithecidae.

4.1.2. Comparison of Trade in Various Wildlife Species

Data obtained from the CITES trade database were again used, coded using Matlab, to classify the trade counts from the species perspective and sorted in order from smallest to largest, and the top 16 species were taken to draw a cluster bar chart to make the results more intuitive. As shown in Figure 2.

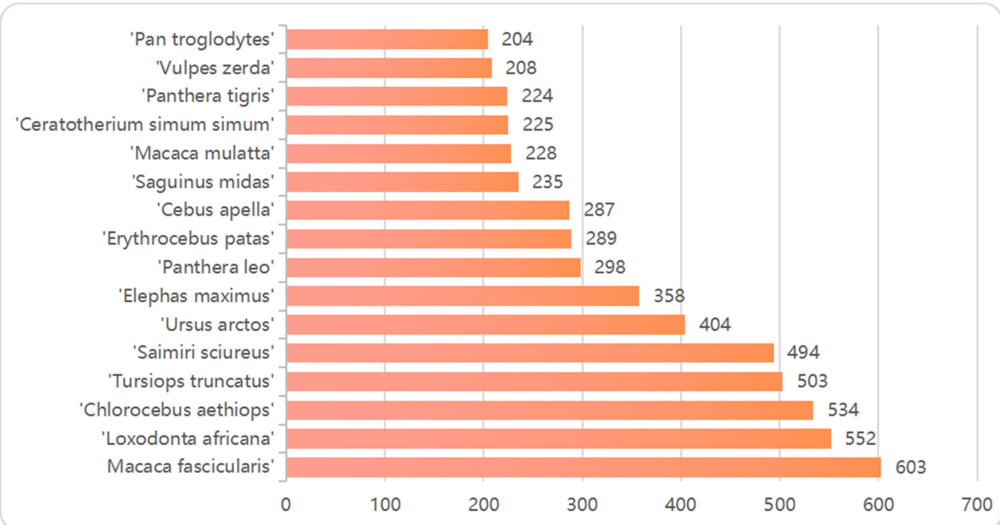

Figure 2. Comparison of trade volumes by wildlife species, 1990-2021

According to the above figure, the species that has been traded the most in the last 30 years, according to the species perspective classification statistics, is Macaca fasciculars, with a total trade of 603, which differs from Loxodonta africana, which is in second place with a total trade of 552.

4.2. Problem 2 Solution

4.2.1. Purpose of Trade Analyzed

According to the reference *A guide to using the CITES Trade Database*, we selected 12 animal trade purposes and extracted the data. To make the subsequent comparative analysis of the

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data more convenient, the main letters are capitalized instead of each purpose selected. The animal trade purpose corresponding to each of these capital letters is as follows.

- B: Breeding in captivity or artificial propagation
- E: Educational
- G: Botanical garden
- H: Hunting trophy
- L: Law enforcement / judicial / forensic
- M:Medical(including biomedical research)
- N:Reintroduction or introduction into the wild
- P:Personal
- Q:Circus or travelling exhibition
- S:Scientific
- T:Commercial
- Z:Zoo

4.2.2. Comparison of the Number of Trade Purposes Selected

The respective numbers of the 12 animal trade items selected above were grouped and sorted from largest to smallest, and a cluster bar graph was drawn. As shown in Figure 3.

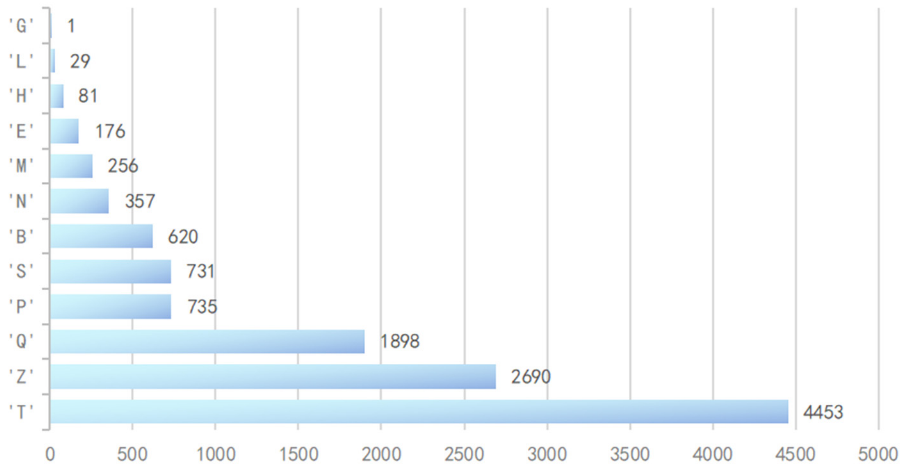

Figure 3. 12 kinds of animal trade cause respective trade volume comparison chart

From the above graph, the highest number of animal trade occurred due to Commercial, with a total of 4453, which is much larger than the animal trade due to other reasons. The trade volume for Zoo purposes is also very high, reaching 2690, and the trade volume due to Circus or traveling exhibition is 1898. Only these three purposes led to a trading volume of more than 1000, so these three purposes are the main causes of animal trade.

4.3. Problem 3 Solution

4.3.1. Analysis of Changes in Total Trade Volume

Using the CITES trade database, we extracted the total animal trade data from 2003 to 2021. To more visually reflect the changes in total trade over these 20 years, we plotted bar charts and added trend lines, as shown in Figure 4.

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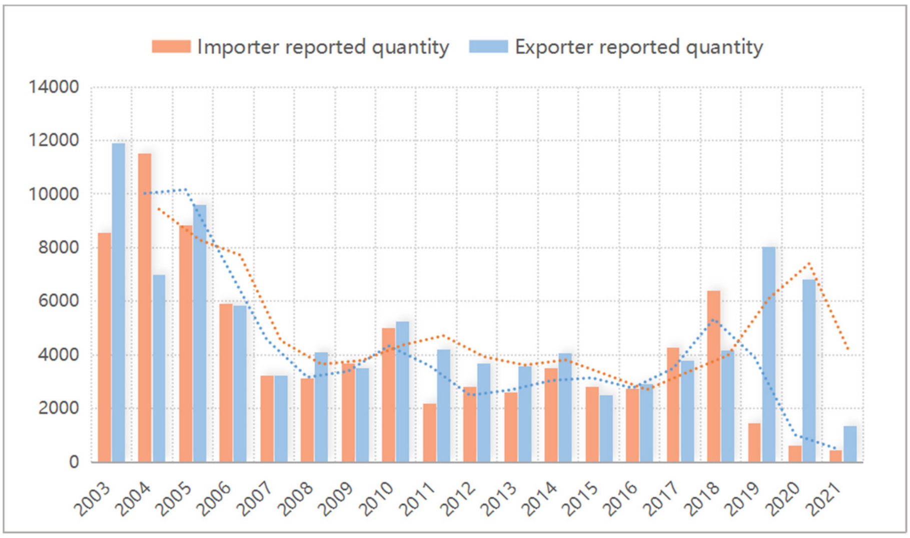

Figure 4. Changes in total animal trade by the year 2003-2021

The data and images show that the most frequent years of trade transactions in the last 20 years were from 2003 to 2005, and the total annual trade volume from 2006 to 2018 was significantly lower. From 2003 to 2018, the Imported reported quantity and the Exporter reported quantity are relatively flat, but from 2018, the Imported reported quantity starts to drop sharply, both below 2000. The Exporter reported quantity decreased slightly, the quantity also remained above 6000 in 2019 and 2020, and sharply decreased to 2000 in 2021. It indicates that the total quantity of animal trade is in a downward trend in the past two decades, and the rate of decline is fast from 2020 to 2021.

4.3.2. Analysis of Changes in Trade Groups

We further subdivided the data to classify the trade data from the perspective of groups. A line graph was also drawn to more visually represent the changes in the number of animals traded by groups over the last 20 years, as shown in Figure 5.

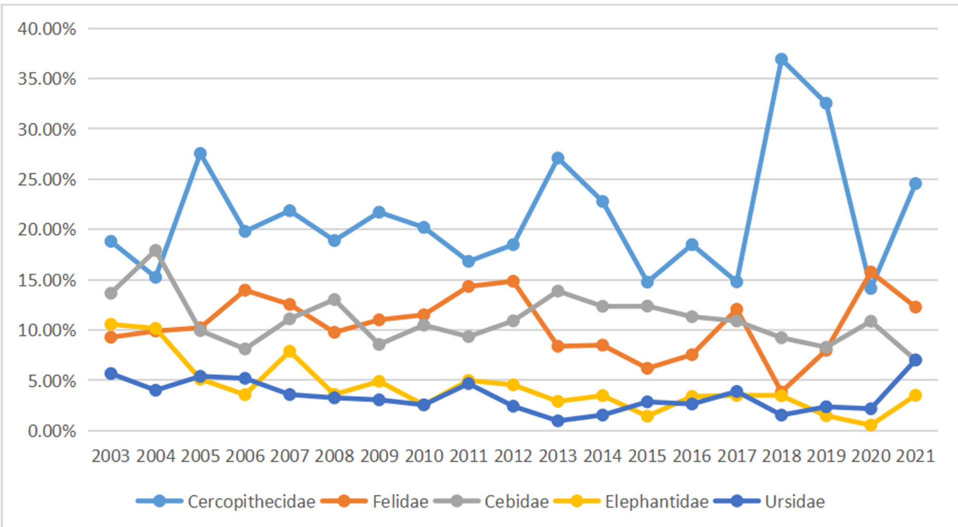

Figure 5. 2003-2021, the change in the trade volume of various animal groups

According to the above figure, according to the group perspective, the group that has been traded the most in the past 20 years is Cercopithecidae, and even reached more than 35% of the total trade in 2018, although the annual trade share fluctuates less, Cercopithecidae has been in the position of the largest share. Elephantidae and Ursida are in the lowest position

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with similar annual trade shares. However, from 2020 to 2021, Elephantidae and Ursida show an increasing trend, while Felidae and Cebidae both show a decreasing trend.

4.3.3. Analysis of Trade Purposes

We also analyzed the animal trade from the point of view of trade purposes, using Matlab to analyze the data for trade purposes. And draw a line graph to more visually reflect the change in each trade purpose in the last 20 years. As shown in Figure 6.

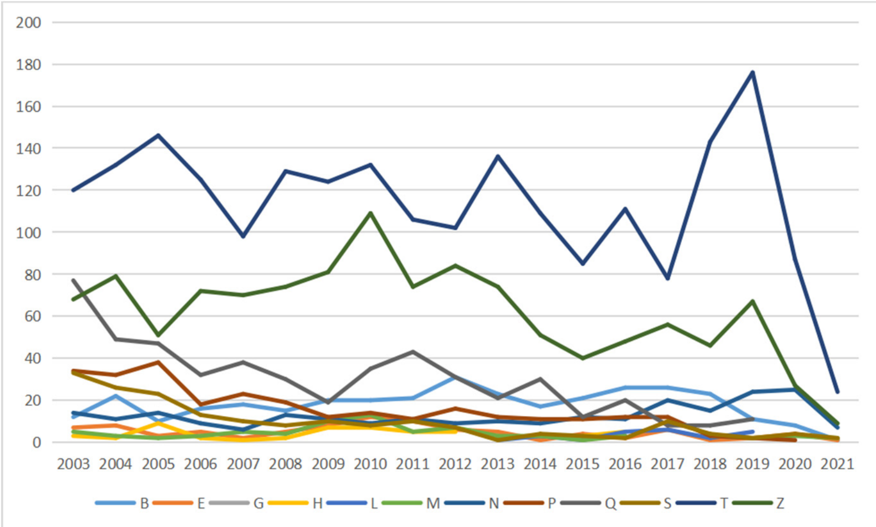

Figure 6. 2003-2021, the number of trade purposes change chart

According to the above chart, the number of animal trade due to Commercial is the largest, much larger than the number of animal trade due to other reasons, and the number even reached 180 in 2019. The next reason is Zoo, the number of animal trade due to other reasons is between 0 and 40 per year, with less fluctuation. Commercial and Zoo trade numbers are relatively more volatile, especially from 2019 to 2021 the number of trade for each purpose is in a state of decline, with Commercial directly from 180 to 20.

5. The Relationship between Wildlife Trade and Major Infectious Disease Outbreaks

5.1. Indicator Determination

In order to study the relationship between wildlife trade and major infectious disease epidemics, we need to quantify wildlife trade and major infectious disease epidemics and find the intrinsic relationship by analyzing relevant index data. By reviewing the literature and relevant data websites, combined with the data provided by the CITES trade database, we finally determined the overall trade amount as the indicator of wildlife trade and the total number of major infectious disease incidences as the indicator of the major infectious disease epidemic and applied Pearson Correlation to determine the relationship between them.

5.2. Model Principle

Pearson Correlation is a way to measure the similarity of vectors. The output ranges from -1 to +1, where 0 represents no correlation, negative values represent negative correlation, and positive values represent positive correlation. The Pearson Correlation coefficient is optimized over the Euclidean distance, and the values of the vectors are centralized. The calculation steps are as follows.

- Suppose there are two sets of data $X{:}\{X_1, X_2, \cdots, X_n\}$ and $Y{:}\{Y_1, Y_2, \cdots, Y_n\}$, first calculate the sample mean and covariance.

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$$\bar{X} = \frac{\sum_{i=1}^{n} X_i}{n}, \bar{Y} = \frac{\sum_{i=1}^{n} Y_i}{n} \tag{1}$$

$$\mathrm{Cov}(X, Y) = \frac{\sum_{i=1}^{n} (X_i - \bar{X})(Y_i - \bar{Y})}{n - 1} \tag{2}$$

- Get the sample Pearson Correlation r_{XY}:

$$r_{XY} = \frac{\mathrm{Cov}(X, Y)}{S_X S_Y} \tag{3}$$

- where S_X(sigma X) is the sample standard deviation of X:

$$S_X = \sqrt{\frac{\sum_{i=1}^{n} (X_i - \bar{X})^2}{n - 1}} \tag{4}$$

For two vectors X and Y, the meaning of the calculated Pearson Correlation is understood as follows.

- When the correlation coefficient is 0, the two vectors X and Y are not correlated.
- When the value of X increases (decreases) and the value of Y decreases (increases), the two vectors X and Y are negatively correlated with a correlation coefficient between -1.0 and 0.0.
- When the value of X increases (decreases) and the value of Y increases (decreases), the two vectors X and Y are positively correlated with a correlation coefficient between 0.0 and +1.0.

Table 2. Interpretation of the magnitude of the correlation coefficient

Correlation	+	-
No correlation	-0.09 to 0.0	0.0 to 0.09
Weak correlation	-0.3 to -0.1	0.1 to 0.3
Medium correlation	-0.5 to -0.3	0.3 to 0.5
Strong correlation	-1.0 to -0.5	0.5 to 1.0

5.3. Operation Process

5.3.1. Scatter Plotting

We first scatter-plotted the data and found a linear correlation between the overall trade amount and the total number of major infectious disease incidences, which helped us to observe the correlation between the variables more intuitively, which made it easier for us to judge.

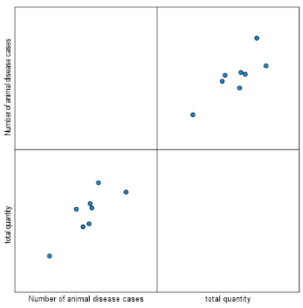

Figure 7. Matrix scatterplot

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5.3.2. Descriptive Statistics

We first performed data correlation, combining the minimum maximum, mean, standard deviation, skewness, kurtosis, and calculated descriptive statistics for the overall trade amount and the total number of major infectious disease incidences, with the following results.

Table 3. Descriptive statistics results

	N	Min	Max	Mean	Standard deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Standard error	Statistic	Standard error
Number of animal disease cases	8	1536255	4610025	3083158.13	861048.317	-0.053	0.752	2.112	1.481
total quantity	8	1761	10582.724	6966.7155	2743.090733	-0.774	0.752	0.89	1.481
Number of effective cases (in columns): 8									

5.3.3. Calculation of Pearson Correlation

Next, we use the corrcoef function in Matlab tools to calculate the correlation coefficients between the two main indicators, and the results are calculated as follows.

	Number of animal disease cases	total quantity
Number of animal disease cases	1	0.823
total quantity	0.823	1

Figure 8. Correlation coefficient between overall trade volume and total number of major infectious disease incidences

5.3.4. Hypothesis Testing

We use the SPSS software to help us obtain the coefficients for hypothesis testing, and the main steps are as follows.

- Propose the original hypothesis H_0 and the alternative hypothesis H_1:

$$H_0: r = 0, H_1: r \neq 0 \tag{5}$$

- Under the condition that the original hypothesis holds, construct the statistic:

$$t = r\sqrt{\frac{n-2}{1-r^2}} \tag{6}$$

- Test values are obtained:

Table 4. Correlation test table

		Number of animal disease cases	total quantity
Number of animal disease cases	Pearson Correlation	1	.823*
	Significance (two-tailed)		0.012
	Number of cases	8	8
total quantity	Pearson Correlation	.823*	1
	Significance (two-tailed)	0.012	
	Number of cases	8	8
*** At the 0.05 level (two-tailed), the correlation is significant.**			

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5.4. Analysis of Results

We finally obtained coefficients > 0.8 between both variables of overall trade amount and major infectious disease incidence, indicating a strong positive correlation between the two. Therefore, we can conclude that there is a positive correlation between wildlife trade and major infectious disease outbreaks when combined with reality. The process of wildlife trade can cause the wide spread of infectious disease pathogens, spreading around the world, expanding the impact of infectious diseases and increasing the threat of infectious diseases to people's lives and health.

6. The Economic and Social Impact of a Long-term Ban on Wildlife Trade

6.1. Indicator Determination

In order to better explore the economic and social impacts of a long-term ban on wildlife trade, we first quantify the economic and social performance and thus reflect how a long-term ban on wildlife trade affects both, and then present our own views based on the results of our analysis. We chose to use the number of animals traded as an indicator of animal trade, global GDP, and fur industry income as economic indicators related to animal trade, and global mortality as a social indicator.

6.2. Model Principle

6.2.1. Multiple Linear Regression Model

Multiple regression analysis is a method to build a prediction model for forecasting by analyzing the correlation between two or more independent variables and a dependent variable. When there is a linear relationship between the independent variables and the dependent variable is called multiple linear regression analysis.

It is assumed that the explanatory variable y has a linear relationship with multiple explanatory variables $x_1, x_2, \cdots, x_k$, and is multiple linear functions of the explanatory variables, i.e.

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k + \mu \tag{7}$$

where y is the explanatory variable, $x_i(i = 1,2, \cdots k)$ is the k explanatory variables, PartialRegression Coeficient $\beta_i(i = 1,2, \cdots k)$ is the k unknown parameters, and β_0 is the constant term. μ is the random error term. For n observations, the set of equations takes the form:

$$Y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \cdots + \beta_k x_{ki} + \mu_{i\%} \tag{8}$$

PartialRegression Coeficient $\beta_i(i = 1,2, \cdots k)$ are unknown and can be estimated using the sample observations $(X_{1i}, X_{2i}, \cdots X_{ki}, Y_i)$. If the calculated parameter estimates are $\hat{\beta}_0, \hat{\beta}_1, \cdots, \hat{\beta}_k$ and the position parameters $\beta_0, \beta_1, \cdots, \beta_k$ in the overall regression equation are replaced by the parameter estimates, the multiple linear regression equation is:

$$\hat{Y}_i = \hat{\beta}_0 + \hat{\beta}_1 x_{1i} + \cdots \hat{\beta}_k x_{ki} \tag{9}$$

where $\hat{\beta}_i(i = 1,2, \cdots k)$ is the parameter estimate and $\hat{Y}_i(i = 1,2, \cdots k)$ is the regression or fitted value of Y_i. The deviation between the estimated value of the explanatory variable $\hat{Y}_i$ obtained from the sample regression equation and the observed value $\hat{Y}_i$ is called the residual e_i.

$$e_i = Y_i - \hat{Y}_i = Y_i - \left(\hat{\beta}_0 + \hat{\beta}_1 x_{1i} +, \cdots, \hat{\beta}_k x_{ki}\right) \tag{10}$$

6.2.2. Parameter Estimation of Multiple Linear Regression Models

The parameter estimation of the multiplex regression model, like the linear regression equation, is also based on the least squares method of solving the parameters under the premise that the sum of squared errors is required to be minimized.

Taking the bilinear regression model as an example, the standard set of equations for the regression parameters is solved and obtained as b.

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$$\begin{cases} \sum y = nb_0 + b_1\sum x_1 + b_2\sum x_2 \\ \sum x_1 y = b_0\sum x_1 + b_1\sum x_1^2 + b_2\sum x_1 x_2 \\ \sum x_2 y = b_0\sum x_2 + b_1\sum x_1 x_2 + b_2\sum x_2 \quad {}^{2} \end{cases} \tag{11}$$

$$b = (x'x)^{-1} \cdot (x'y) \tag{12}$$

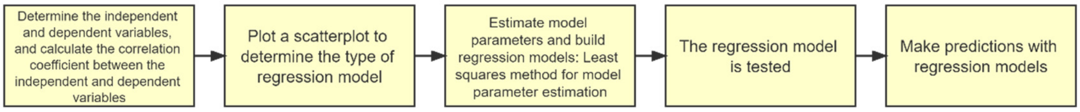

Figure 9. Multiple linear regression analysis logic

6.3. Model Solving

Here we use the SPSS tool to assist us in completing the multiple linear regression analysis.

6.3.1. Scatter Plot Approximate Judgment

Before the multiple linear regression analysis, it is necessary to make a visual determination of whether the data are linear or not. We first make a matrix correlation chart to take us to visualize the relationship between the four main indicators of global GDP, fur industry income, global mortality and animal trade volume.

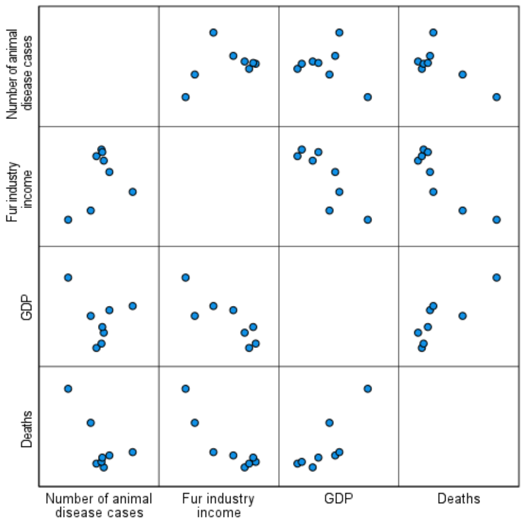

Figure 10. Matrix Correlation Chart

6.3.2. Calculation of the Degree of Linear Fit

After setting the parameters using SPSS tool, we tested the degree of linear fit of the indicators and the independence of the dependent variables. R-square represents the degree of linear fit, the closer to 1 the better; Durbin-Watson index indicates the independence between the dependent variables, the closer to 2 the better. The results of this operation are as follows.

Table 5. Test results

Model	R	R-square	Adjusted R-squared	Errors in standard estimation	Durbin Watson
1	.939a	0.881	0.793	392177.855	1.931

6.3.3. Normality Test

We used SPSS to plot histograms and standard P-P plots of regression standardized residuals for normality tests. This shows that the variables are close to normal and the linear regression can be made under the approximate normal condition.

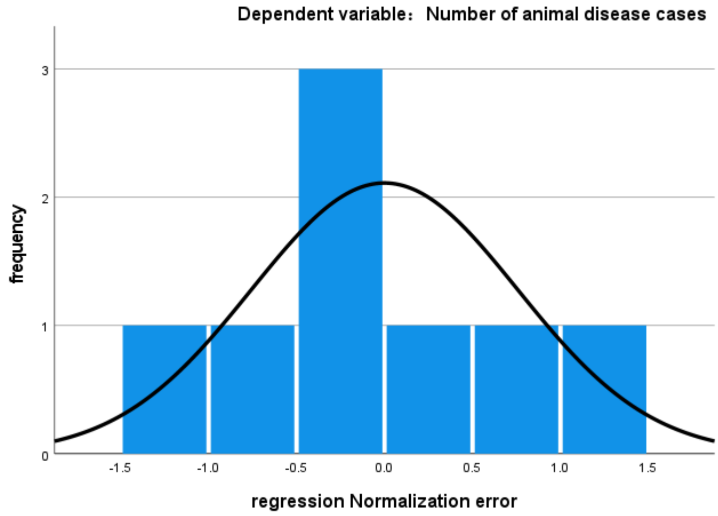

Figure 11. Histogram

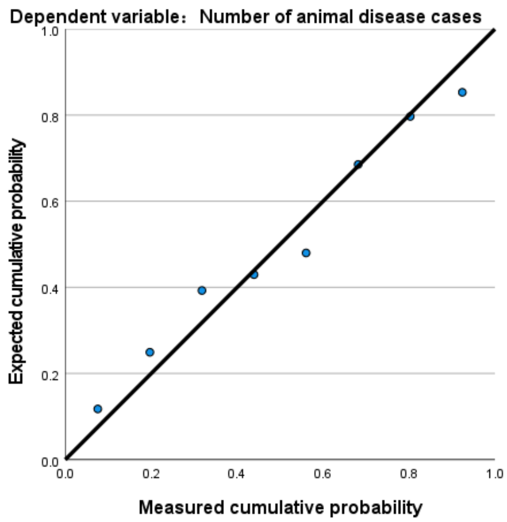

Figure 12. Standard P-P plot of regression-standardized residuals

6.3.4. Significance Test of the Regression Equation

We used SPSS to test the significance of the regression equation and obtained the following results. the larger the F, the more significant the regression equation is; Sig, the significance, sig<0.05, is considered significant. The significance of this result is significant.

Table 6. Significance test

Model		Sum of square	Degree of freedom	Mean Square	F	Significance
1	Returning	4.57462E+12	3	1.52487E+12	9.914	.025b
	Residual	6.15214E+11	4	1.53803E+11		
	Total	5.18983E+12	7			

6.3.5. Significance Test of Regression Coefficients

We can see by the significance test of the regression coefficients that indicate that there is a significance test variance inflation factor <10 between all variables, indicating that there is no cointegration problem in the data.

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Table 7. Significance test of regression coefficients

Model		Unstandardized factor		Standardization factor	t	Significance	Covariance statistics	
		B	Standard error	Beta			tolerance	VIF
1	(Constant)	19997420.21	5742285.57		3.482	0.025		
	Fur industry income	-3291.93	1591.541	-0.874	-2.068	0.107	0.166	6.024
	GDP（Trillion dollars）	76306.741	42977.534	0.602	1.776	0.15	0.258	3.883
	Dead population（Thousands）	-353.771	71.064	-1.978	-4.978	0.008	0.188	5.326

6.4. Analysis of Results

Based on these results, we can see that the economic and social impacts of a long-term ban on wildlife trade are significant. According to the literature, a long-term ban on wildlife trade will cause economic losses in the short term, for example, a ban on wild meat consumption may cost China's economy 50 billion RMB ($7.1 billion) and put 1 million people out of work, or reduce the original source of fur garments and reduce the income of the fur market, thus affecting the economy. In the long run, however, a long-term ban on wildlife trade would be beneficial to the sustainable development of the economy and society, optimize the industrial structure of the economy, and reduce the spread of animal disease pathogens, thus contributing to the green health of the economy and society.

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