

**MS Contribution to:** Lee, C. (2019). China's Energy Diplomacy: Does Chinese Foreign Policy Favor Oil-Producing Countries? Foreign Policy Analysis, 15(4), 570–588. <https://doi.org/10.1093/fpa/orz011>

Applied Stats II  
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Due: March 31, 2024

## 1 Twist 1: Plots

Loading the data:

```
1 data_part <- read.csv("data_partner.csv") # Data on China's diplomatic
  partnerships (cross-national data)
2 data_TSCS <- read.csv("data_TSCS.csv") # Data on China's aid to Africa (TSCS
  data)
3 data_aid <- read.csv("data_aid.csv") # Data on China's aid to Africa (cross-
  national data)
4 data_visit <- read.csv("data_visit.csv") # Data on China's leadership visits (
  cross-national data)
```

### Figure 2 Twist:

On p. 581, Lee presents four plots (Figure 2: 'I select four African oil-producing countries that have received Chinese aid (**Angola, Cameroon, Nigeria, Tunisia** — MS) , and graphically present the amount of aid received and their oil production from 2000 to 2013 in figure 2. As shown in figure 2, Chinese aid (denoted by the solid line) fluctuates from year to year, whereas oil production (denoted by the dashed line) is relatively stable over time. Angola, for example, received more than 2 billion dollars from China in 2005, 2007, and 2011 each but none in 2000 or 2009. In other words, if the time-serial variation is taken into account, the results may be confounded by the volatility of Chinese aid. Because the annual aid amount is subject to the Chinese government's yearly budget, it is less likely that it will clearly follow aid recipients' oil production every year. *When I only focus on the variation across African countries, however, it is observed that **African oil producers in general receive more Chinese aid than non-oil producers.***

My idea was to test this last finding, therefore I randomly chose one non-oil producing state from each of the five UN African regions: **Morocco** from Northern Africa, **Senegal**

from Western Africa, **Central African Republic** from Central Africa, **Burundi** from Eastern Africa, and **Botswana** from Southern Africa, and created similar plots of the amount of Chinese aid receives over their oil production 2000-2013 (which is denoted as 0 in this dataset). I also plotted one other major African oil-producer, Sudan, which was not included in Lee's initial analysis, to compare with the non-oil producers. **Overall. Lee's findings were proved to be correct: if focused on the variation across African countries, it is indeed observed that African non-oil producers receive notably less Chinese aid than oil-producers.**

```

1 africa <- subset(data_TSCS, africa==1 & year>1999)
2 africa <- cbind(africa["country"], africa["year"], africa["china_aid"], africa
  ["production2"])
3 africa$china_aid <- ifelse(is.na(africa$china_aid)==T, 0, africa$china_aid)
4 africa <- africa[order(africa$country, africa$year), ]
5
6 Morocco <- subset(africa, country == "Morocco")
7 Senegal <- subset(africa, country == "Senegal")
8 CAR <- subset(africa, country == "Central African Republic")
9 Burundi <- subset(africa, country == "Burundi")
10 Botswana <- subset(africa, country == "Botswana")
11 Sudan <- subset(africa, country == "Sudan")
12
13 par(mar=c(4,3,2,3), mfrow=c(2, 3))
14
15 #Northern Africa: Morocco
16 plot(Morocco$china_aid/1000000 ~ Morocco$year, type="l", lwd=4, xlab="", ylab=
  "", ylim=c(0, 500), axes=F, main="Northern Africa: MOROCCO")
17 axis(1, at= Morocco$year, label= Morocco$year, cex.axis=1.2)
18 axis(2, at=seq(0, 500, by=100), label=seq(0, 500, by=100), cex.axis=1.2)
19 par(new=T)
20 plot(Morocco$production2/1000 ~ Morocco$year, type="l", lwd=4, lty=9, xlab="",
  ylab="", ylim=c(0, 200), axes=F)
21 axis(4, at=seq(0, 200, by=50), label=seq(0, 200, by=50), cex.axis=1.2)
22 box()
23 legend("topleft", c("Chinese aid (millions)", "Oil production (KBPD)"), cex
  =1.3, lwd=4, lty=c(1, 9))
24
25 #Western Africa: Senegal
26 plot(Senegal$china_aid/1000000 ~ Senegal$year, type="l", lwd=4, xlab="", ylab=
  "", ylim=c(0, 500), axes=F, main="Western Africa: SENEGAL")
27 axis(1, at= Senegal$year, label= Senegal$year, cex.axis=1.2)
28 axis(2, at=seq(0, 500, by=100), label=seq(0, 500, by=100), cex.axis=1.2)
29 par(new=T)
30 plot(Senegal$production2/1000 ~ Senegal$year, type="l", lwd=4, lty=9, xlab="",
  ylab="", ylim=c(0, 200), axes=F)
31 axis(4, at=seq(0, 200, by=50), label=seq(0, 200, by=50), cex.axis=1.2)
32 box()
33 legend("topleft", c("Chinese aid (millions)", "Oil production (KBPD)"), cex
  =1.3, lwd=4, lty=c(1, 9))
34

```

```

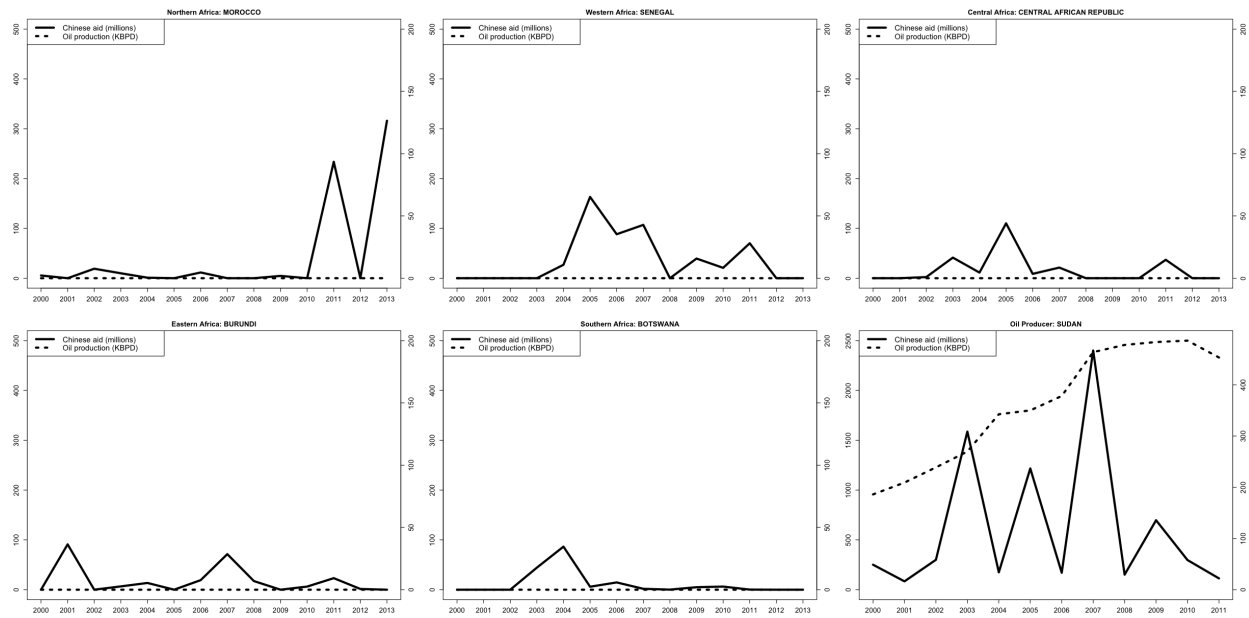
35 #Central Africa: Central African Republic
36 plot(CAR$china_aid/1000000 ~ CAR$year, type="l", lwd=4, xlab="", ylab="", ylim
      =c(0, 500), axes=F, main="Central Africa: CENTRAL AFRICAN REPUBLIC")
37 axis(1, at= CAR$year, label= CAR$year, cex.axis=1.2)
38 axis(2, at=seq(0, 500, by=100), label=seq(0, 500, by=100), cex.axis=1.2)
39 par(new=T)
40 plot(CAR$production2/1000 ~ CAR$year, type="l", lwd=4, lty=9, xlab="", ylab=""
      , ylim=c(0, 200), axes=F)
41 axis(4, at=seq(0, 200, by=50), label=seq(0, 200, by=50), cex.axis=1.2)
42 box()
43 legend("topleft", c("Chinese aid (millions)", "Oil production (KBPD)"), cex
      =1.3, lwd=4, lty=c(1, 9))
44
45 #Eastern Africa: Burundi
46 plot(Burundi$china_aid/1000000 ~ Burundi$year, type="l", lwd=4, xlab="", ylab=
      "", ylim=c(0, 500), axes=F, main="Eastern Africa: BURUNDI")
47 axis(1, at= Burundi$year, label= Burundi$year, cex.axis=1.2)
48 axis(2, at=seq(0, 500, by=100), label=seq(0, 500, by=100), cex.axis=1.2)
49 par(new=T)
50 plot(Burundi$production2/1000 ~ Burundi$year, type="l", lwd=4, lty=9, xlab="",
      ylab="", ylim=c(0, 200), axes=F)
51 axis(4, at=seq(0, 200, by=50), label=seq(0, 200, by=50), cex.axis=1.2)
52 box()
53 legend("topleft", c("Chinese aid (millions)", "Oil production (KBPD)"), cex
      =1.3, lwd=4, lty=c(1, 9))
54
55 #Southern Africa: Botswana
56 plot(Botswana$china_aid/1000000 ~ Botswana$year, type="l", lwd=4, xlab="",
      ylab="", ylim=c(0, 500), axes=F, main="Southern Africa: BOTSWANA")
57 axis(1, at= Botswana$year, label= Botswana$year, cex.axis=1.2)
58 axis(2, at=seq(0, 500, by=100), label=seq(0, 500, by=100), cex.axis=1.2)
59 par(new=T)
60 plot(Botswana$production2/1000 ~ Botswana$year, type="l", lwd=4, lty=9, xlab=""
      , ylab="", ylim=c(0, 200), axes=F)
61 axis(4, at=seq(0, 200, by=50), label=seq(0, 200, by=50), cex.axis=1.2)
62 box()
63 legend("topleft", c("Chinese aid (millions)", "Oil production (KBPD)"), cex
      =1.3, lwd=4, lty=c(1, 9))
64
65 #Bonus: oil-producing Sudan
66 plot(Sudan$china_aid/1000000 ~ Sudan$year, type = "l", lwd = 4, xlab = "",
      ylab = "", ylim = c(0, 2500), axes = FALSE, main = "Oil Producer: SUDAN")
67 axis(1, at = Sudan$year, label = Sudan$year, cex.axis = 1.2)
68 axis(2, at = seq(0, 2500, by = 500), label = seq(0, 2500, by = 500), cex.axis
      = 1.2)
69 par(new = TRUE)
70 plot(Sudan$production2 ~ Sudan$year, type = "l", lwd = 4, lty = 9, xlab = "",
      ylab = "", ylim = c(0, max(Sudan$production2, na.rm = TRUE)), axes = FALSE
      )
71 axis(4, at = seq(0, max(Sudan$production2, na.rm = TRUE), by = 100), label =
      seq(0, max(Sudan$production2, na.rm = TRUE), by = 100), cex.axis = 1.2)

```

```

72 box()
73 legend("topleft", c("Chinese aid (millions)", "Oil production (KBPD)"), cex =
    1.3, lwd = 4, lty = c(1, 9))

```



### Model 1 Twist:

Lee, p. 576: 'To test the first hypothesis (China is more likely to build partnerships with countries abundant in energy resources — MS), I use data on China's partnerships. Beijing considers three types of partnerships—partnerships, strategic partnerships, and comprehensive strategic partnerships. [...]. A country is coded as 1 as long as it has a partnership connection with China, regardless of the type' Lee, p. 579-580: '... the sample includes 125 developing countries. Developed countries (i.e., OECD members) are excluded from the sample because their relationships and interactions with China may follow a different pattern. All the independent and control variables enter the model at their mean values between 1992 and 2012.'. 'As can be seen, the coefficient for oil production is positive and statistically significant at the 5 percent level. This means that **China is more likely to build partnerships with oil-producing countries.**'. 'In other words, energy abundance plays an important role in determining Beijing's partnership building. In addition to oil production, FDI has a strong, positive effect in models 1 and 2, meaning that **China is more likely to form partnerships with countries that receive more FDI.** Trade importance is also positively associated with the formation of strategic or comprehensive strategic partnerships (Model 2 — MS). These findings show that **China's partnership diplomacy is largely driven by economic considerations.**'

While original binomial logit Model 1 includes a binary dependent variable on partnership (0, 1), the dataset itself has more detailed data on the type of partnerships that China has with the non-OECD countries. It includes dummy variables for each of the three types of partnerships: **partnership, strategic partnership, comprehensive strategic partnership.** My understanding is that these types of partnership are following a certain order, though it might not be the case. My idea was to fit an unordered and ordered logit models with the same dependent variable (though relevelled accordingly for each of the models) and predictors, to test whether they would deliver any additional insights or be of better fit to the data.

I exponentiated the coefficients for all the models for better clarity, and calculated predicted probabilities to fit confusion matrices, which also helped with establishing the accuracy score of the models. I also estimated the models' statistics, such as **residual deviance** (how much probabilities estimated from our model differ from the observed proportions of successes), **Akaike Information Criterion** and **Bayesian Information Criterion** (goodness of fit measures), and performed a **Brant test** on the ordered model to establish whether the "proportional odds assumption" holds in its case.

The following conclusions can be driven from my "twist":

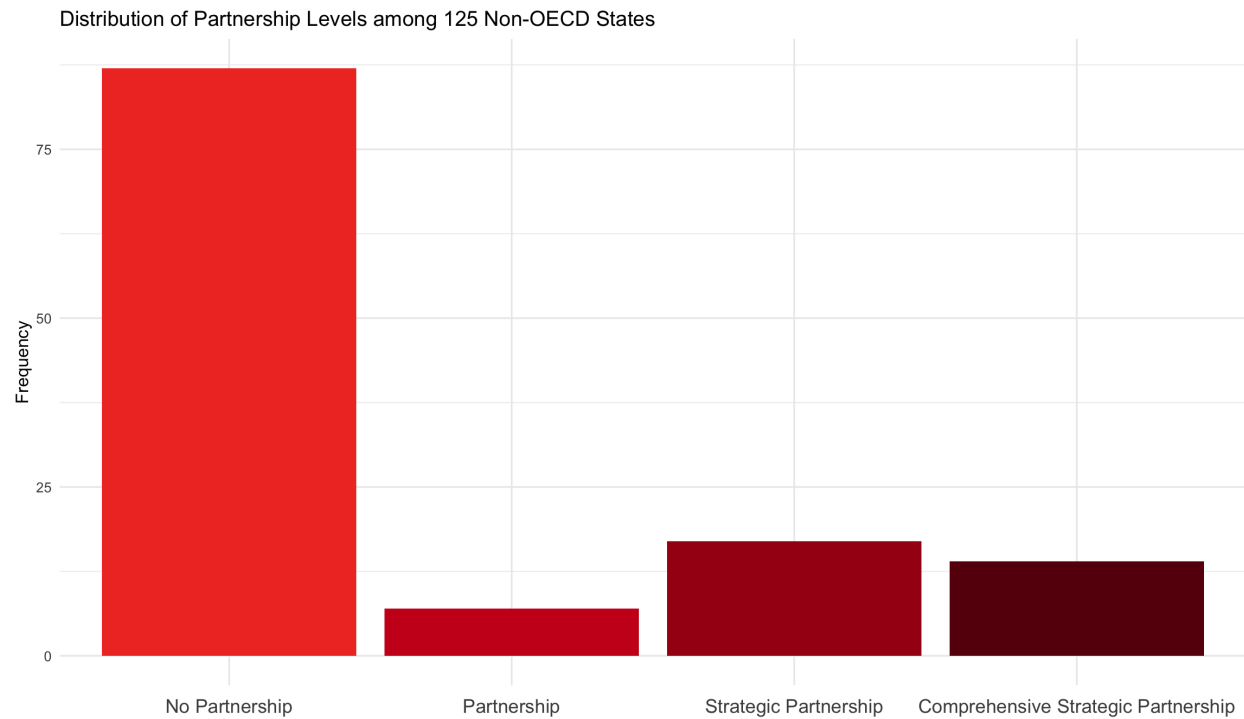
- New models confirmed the initial findings that China is more likely to build partnerships with countries abundant in energy resources + it is also driven by economic considerations (significant coefficients for Oil production, FDI inflows, Trade importance).
- Both new models performed reasonably efficiently as compared to the initial binomial model, though the ordered model achieved a higher accuracy score and coefficients more similar in value.

- Parallel Regression Assumption (PRA) holds for the ordered model, which makes it a more adequate fit for the data.
- Interesting experiment overall, BUT: the original binomial logit Model 1 is still the most accurate → we might assume that being China's partner versus not being China's partner at all carries greater significance compared to being involved in a specific type of partnership.

```

1 #PREPARING THE DATA
2
3 #1
4 #Model 1 dropped 4 observations from the 'subset(data_part, oecd==0)' (129),
5 #so there were 125 states left. After re-checking with the Table A2, and
6 #manually,
7 #we know that the 4 states dropped are: Cuba, Kyrgyzstan, Somalia, South Sudan
8
9 #Subsetting 125 non-OECD members
10 data_part <- subset(data_part, !(country %in% c("Cuba", "Kyrgyzstan", "Somalia",
11 "South Sudan")))
12 data_part125 <- subset(data_part, oecd==0)
13
14 #2
15 #Creating new column for the partnership level
16 data_part125$partlevel <- NA
17
18 #Combining partnership levels (dummy variables) into one column
19 data_part125$partlevel[data_part125$part == 1] <- "Partnership"
20 data_part125$partlevel[data_part125$part2 == 1] <- "Strategic Partnership"
21 data_part125$partlevel[data_part125$part3 == 1] <- "Comprehensive Strategic Partnership"
22 data_part125$partlevel[is.na(data_part125$partlevel)] <- "No Partnership"
23
24 #Recoding 'partlevel' into a categorical variable (as factor), unordered (for now),
25 #with reference category being "No Partnership"
26 data_part125$partlevel <- relevel(factor(data_part125$partlevel),
27 ref = "No Partnership")
28
29 #Bar plot for 'partlevel'
30 color_palette <- brewer.pal(9, "Reds")[6:9] #Custom color palette in dark red colours
31 ggplot(data_part125, aes(x = factor(partlevel, levels = c("No Partnership", "Partnership", "Strategic Partnership", "Comprehensive Strategic Partnership")))) +
32   geom_bar(fill = color_palette) +
33   labs(title = "Distribution of Partnership Levels among 125 Non-OECD States",
34         x = "",
35         y = "Frequency") +
36   theme_minimal() +
37   theme(axis.text.x = element_text(size = 12, vjust = -0.5))

```



```

1 #ORIGINAL MODEL 1 (DV: Partnership: 0 for no partnership ,
2 #1 for partnership (any kind))
3 #Binomial logit regression. OECD countries excluded
4 modell <- glm(partner~prod2+GDPpc2+growth2+FDI2+trade.de2+polity2+dom2+usally2
5 , family=binomial, data = data_part125)
6 summary(modell)
7 #Exponentiating coefficients (to OR).
8 #Checking again by adding confidence intervals;
9 #CI should not contain 1 for a significant result (odds either below or above
10 1)
11 exp_modell <- exp(cbind(OR = coef(modell), confint(modell)))
12 print(round(exp_modell, 3))
13 stargazer(exp_modell, type="latex", t.auto=F); logLik(modell)

```

Table 1: Original Model 1 (exponentiated)

	<i>Dependent variable:</i>
	Partnership
Oil production	1.139** (0.058)
GDP per capita	0.715 (0.270)
GDP growth	0.968 (0.089)
FDI inflows	1.299*** (0.081)
Trade importance	3.678 (0.826)
Level of democracy	0.993 (0.051)
Domestic conflict	1.223 (0.138)
US ally	0.398 (0.777)
Constant	0.012** (2.226)
Observations	125
Log Likelihood	−55.546
Residual Deviance	111.09
AIC	129.091
BIC	154.5459
<i>Note:</i>	*p<0.1; **p<0.05; ***p<0.01



```

1 #Calculating predicted probabilities and converting it to a factor,
2 #where a probability <0.05 = 0 (no partnership), >0.5 = 1 (partnership)
3 predprob_model1 <- factor(ifelse(predict(model1, type = "response") > 0.5, 1,
4                                0), levels = c(0, 1))
5 #Converting the dependent variable into factor
6 data_part125$partner <- factor(data_part125$partner)
7 #Confusion matrix
8 cm_model1 <- confusionMatrix(predprob_model1, data_part125$partner)
9 cm_model1 #Accuracy score 0.784

```

#### Confusion Matrix and Statistics

```

              Reference
Prediction 0  1
0      78 18
1       9 20

      Accuracy : 0.784
      95% CI : (0.7015, 0.8526)
No Information Rate : 0.696
P-Value [Acc > NIR] : 0.01828

      Kappa : 0.4531

McNemar's Test P-Value : 0.12366

      Sensitivity : 0.8966
      Specificity : 0.5263
      Pos Pred Value : 0.8125
      Neg Pred Value : 0.6897
      Prevalence : 0.6960
      Detection Rate : 0.6240
      Detection Prevalence : 0.7680
      Balanced Accuracy : 0.7114

      'Positive' Class : 0

```

```

1 #UNORDERED MODEL. OECD countries excluded.
2 unordmodel <- multinom(partlevel ~ prod2+GDPpc2+growth2+FDI2+
3                        trade.de2+trade.de2+polity2+dom2+usally2 ,
4                        data_part125)
5 summary(unordmodel)
6
7 #Calculating p-values to estimate significance of the coefficients
8 coefs <- coef(unordmodel)
9 std_errors <- summary(unordmodel)$standard.errors
10 t_values <- coefs/std_errors
11 df <- nrow(data_part125) - length(coef(unordmodel))

```

```

12 p_values <- 2 * pnorm(abs(t_values), lower.tail = FALSE)
13 p_values < 0.05

```

	(Intercept)	prod2	GDPpc2	growth2	FDI2	trade.de2	polity2	dom2	usally2
Comprehensive Strategic Partnership	FALSE	FALSE	TRUE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE
Partnership	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
Strategic Partnership	FALSE	TRUE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE

```

1 #Exponentiating coefficients (to OR).
2 #Checking again by adding confidence intervals;
3 #CI should not contain 1 for a significant result (odds either below or above
  1)
4 exp_unordmodel <- exp(coef(unordmodel))
5 print(round(exp_unordmodel, 3))
6 stargazer(exp_unordmodel, type="latex", t.auto=F); logLik(unordmodel)

```

Table 2: Unordered Model (exponentiated)

	<i>Dependent variable:</i>		
	Comprehensive Strategic Partnership	Partnership	Strategic Partnership
	(1)	(2)	(3)
Oil production	1.221** (0.104)	1.013 (0.105)	1.197** (0.083)
GDP per capita	0.347** (0.520)	1.004 (0.490)	0.756 (0.363)
GDP growth	1.003 (0.157)	0.864 (0.227)	0.980 (0.103)
FDI inflows	1.885** (0.284)	1.133 (0.148)	1.266** (0.097)
Trade importance	10.218** (1.189)	0.153 (4.021)	2.253 (1.083)
Level of democracy	0.944 (0.087)	1.095 (0.106)	0.973 (0.067)
Domestic conflict	0.957 (0.239)	1.308 (0.236)	1.337 (0.177)
US ally	1.536 (1.268)	0.230 (1.281)	0.288 (1.047)
Constant	0.000 (5.576)	0.008 (3.694)	0.003** (2.928)
Observations	125		
Log Likelihood	-83.263		
Residual Deviance	166.526		
AIC	220.526		
BIC	296.89		

*Note:*

\*p&lt;0.1; \*\*p&lt;0.05; \*\*\*p&lt;0.01

1 #Calculating predicted probabilities

```

2 predprob_unord <- predict(unordmodel, newdata = data_part125, type = "class")
3
4 #Confusion matrix
5 cm_unordmodel <- confusionMatrix(predprob_unord, data_part125$partlevel)
6 cm_unordmodel #Accuracy score 0.744

```

#### Confusion Matrix and Statistics

	Reference			
Prediction	No Partnership	Comprehensive Strategic Partnership	Partnership Strategic Partnership	
No Partnership	81		5	7
Comprehensive Strategic Partnership	3		8	0
Partnership	0		0	0
Strategic Partnership	3		1	0

#### Overall Statistics

Accuracy : 0.744  
 95% CI : (0.6582, 0.8178)  
 No Information Rate : 0.696  
 P-Value [Acc > NIR] : 0.1419

Kappa : 0.3534

McNemar's Test P-Value : NA

#### Statistics by Class:

	Class: No Partnership	Class: Comprehensive Strategic Partnership	Class: Partnership
Sensitivity	0.9310	0.5714	0.000
Specificity	0.3684	0.9640	1.000
Pos Pred Value	0.7714	0.6667	NaN
Neg Pred Value	0.7000	0.9469	0.944
Prevalence	0.6960	0.1120	0.056
Detection Rate	0.6480	0.0640	0.000
Detection Prevalence	0.8400	0.0960	0.000
Balanced Accuracy	0.6497	0.7677	0.500

	Class: Strategic Partnership
Sensitivity	0.2353
Specificity	0.9630
Pos Pred Value	0.5000
Neg Pred Value	0.8889
Prevalence	0.1360
Detection Rate	0.0320
Detection Prevalence	0.0640
Balanced Accuracy	0.5991

```

1 #ORDERED MODEL. OECD countries excluded.
2 #Recoding 'partlevel' into a categorical ORDERED variable (as factor)
3 data_part125$partlevel <- factor(data_part125$partlevel,
4                                   ordered = TRUE,
5                                   levels = c("No Partnership",
6                                               "Partnership",
7                                               "Strategic Partnership"),

```

```

8                                     "Comprehensive Strategic
  Partnership"))
9 #Fitting an ordered model
10 ordmodel<- polr(partlevel~prod2+GDPpc2+growth2+FDI2+
11                 trade.de2+trade.de2+polity2+dom2+usally2 ,
12                 data_part125)
13 summary(ordmodel)
14
15 #Calculating p-values to estimate significance of the coefficients
16 t_values <- coef(summary(ordmodel))[, "t value"]
17 df <- nrow(data_part125) - length(coef(ordmodel))
18 p_values <- 2 * pt(abs(t_values), df = df, lower.tail = FALSE)
19 p_values < 0.05

```

	prod2	GDPpc2
	TRUE	FALSE
	growth2	FDI2
	FALSE	TRUE
	trade.de2	polity2
	TRUE	FALSE
	dom2	usally2
	FALSE	FALSE
No Partnership Partnership		Partnership Strategic Partnership
TRUE		TRUE
Strategic Partnership Comprehensive Strategic Partnership		
TRUE		

```

1 ##Exponentiating coefficients (to OR).
2 #Checking again by adding confidence intervals;
3 #CI should not contain 1 for a significant result (odds either below or above
  1)
4 exp_ordmodel <- exp(cbind(OR = coef(ordmodel), confint(ordmodel)))
5 print(round(exp_ordmodel, 3))
6 stargazer(exp_ordmodel, type="latex", t.auto=F); logLik(ordmodel)

```

Table 3: Ordered Model (exponentiated)

	<i>Dependent variable:</i>
	Partnership Level
Oil production	1.124** (0.057)
GDP per capita	0.694 (0.256)
GDP growth	0.958 (0.086)
FDI inflows	1.324*** (0.078)
Trade importance	6.095** (0.745)
Level of democracy	0.953 (0.050)
Domestic conflict	1.155 (0.131)
US ally	0.841 (0.678)
<i>Intercepts</i>	
No Partnership—Partnership	77.138**
Partnership—Strategic Partnership	118.238**
Strategic Partnership—Comprehensive Strategic Partnership	513.783**
Observations	125
Log Likelihood	−90.19376
Residual Deviance	180.3875
AIC	202.3875
BIC	233.499
<i>Note:</i>	*p<0.1; **p<0.05; ***p<0.01

```

1 #Calculating predicted probabilities
2 predprob_ord <- predict(ordmodel, newdata = data_part125, type = "class")
3
4 #Confusion matrix
5 cm_ordmodel <- confusionMatrix(data = predprob_ord, reference = data_part125$
  partlevel)
6 cm_ordmodel #Accuracy score 0.752

```

### Confusion Matrix and Statistics

Prediction	Reference			
	No Partnership	Partnership	Strategic Partnership	Partnership
No Partnership	82	7		11
Partnership	0	0		0
Strategic Partnership	2	0		4
Comprehensive Strategic Partnership	3	0		2

Prediction	Reference		
	Comprehensive	Strategic	Partnership
No Partnership			4
Partnership			0
Strategic Partnership			2
Comprehensive Strategic Partnership			8

## Overall Statistics

Accuracy : 0.752  
 95% CI : (0.6668, 0.8249)  
 No Information Rate : 0.696  
 P-Value [Acc > NIR] : 0.1016

Kappa : 0.3809

McNemar's Test P-Value : NA

## Statistics by Class:

	Class: No Partnership	Class: Partnership	Class: Strategic Partnership
Sensitivity	0.9425	0.000	0.2353
Specificity	0.4211	1.000	0.9630
Pos Pred Value	0.7885	NaN	0.5000
Neg Pred Value	0.7619	0.944	0.8889
Prevalence	0.6960	0.056	0.1360
Detection Rate	0.6560	0.000	0.0320
Detection Prevalence	0.8320	0.000	0.0640
Balanced Accuracy	0.6818	0.500	0.5991
	Class: Comprehensive Strategic Partnership		
Sensitivity	0.5714		
Specificity	0.9550		
Pos Pred Value	0.6154		
Neg Pred Value	0.9464		
Prevalence	0.1120		
Detection Rate	0.0640		
Detection Prevalence	0.1040		
Balanced Accuracy	0.7632		

```
1 #MODELS STATISTICS
2 #Residual Deviance
3 deviance(unordmodel)
4 deviance(ordmodel)
5 deviance(model1)
```

```
[1] 166.5255
[1] 180.3875
[1] 111.0911
```

```
1 #Akaike Information Criterion (the lower value, the better)
2 AIC(model1)
3 AIC(unordmodel)
4 AIC(ordmodel)
```



```
[1] 129.0911
[1] 220.5255
[1] 202.3875
```

```
1 #Bayesian Information Criterion (the lower value, the better)
2 BIC(model1)
3 BIC(unordmodel)
4 BIC(ordmodel)
```

```
[1] 154.5459
[1] 296.89
[1] 233.499
```

```
1 #Brant test for the ordered model (testing the "proportional odds assumption")
2 brant(ordmodel)
```

Test for	X2	df	probability
Omnibus	15.7	16	0.47
prod2	1.74	2	0.42
GDPpc2	2.55	2	0.28
growth2	-2.46	2	1
FDI2	1.66	2	0.44
trade.de2	3.99	2	0.14
polity2	1.39	2	0.5
dom2	3.42	2	0.18
usally2	3.64	2	0.16

H0: Parallel Regression Assumption holds

## 2 References

Lee, C. (2019). China's Energy Diplomacy: Does Chinese Foreign Policy Favor Oil-Producing Countries? *Foreign Policy Analysis*, **15**(4), 570–588. <https://doi.org/10.1093/fpa/orz011>

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