**A Multilevel Mixed-Effects Approach: Modeling the Determinants of China's Official Financing in Southeast Asia**

**Introduction**

This project examines the factors influencing **China’s Official Financing (COF)** allocations to Southeast Asian countries, focusing on three key dimensions: economic interdependency, territorial disputes, and institutional embeddedness. Using multilevel mixed-effects models, the analysis accounts for variations across countries and years.

**Hypotheses**

1. **Economic Interdependence**:
   * **H1(a)**: A higher proportion of imports from China is associated with increased COF allocations.
   * **H1(b)**: A higher proportion of exports to China is associated with increased COF allocations.
2. **Territorial Disputes and Resolution**:
   * **H2(a)**: Increased territorial dispute intensity is negatively associated with COF allocations.
   * **H2(b)**: Peaceful resolution of territorial disputes is negatively associated with COF allocations.
3. **Institutional Embeddedness**:
   * **H3(a)**: Membership in the Belt and Road Initiative (BRI) is positively associated with COF allocations.
   * **H3(b)**: Membership in the Asian Infrastructure Investment Bank (AIIB) is positively associated with COF allocations.

**Data**

The **dependent variable** in our analysis is the log of COF allocations, which includes Official Development Assistance (ODA), Other Official Flows (OOF), and VOF data.

**Independent variables** include:

* **Trade Dependency**: The percentage of a country’s imports from and exports to China.
* **Dispute Intensity**: Measured using a binary indicator for territorial disputes.
* **Institutional Participation**: Binary indicators for membership in the BRI and AIIB.

Control variables include GDP per capita, population size, political stability, and non-permanent membership in the United Nations Security Council (UNSC).

Model Building Steps and R Code

I only use **multilevel mixed-effects models** for economic interdependency as an example of model building. The random intercept model allows for varying intercepts by country, capturing country-specific baseline levels of COF.

**Step 1: Load Packages and Data**

# Load necessary libraries

library(lme4) # For mixed-effects modeling

library(readxl) # To read Excel data

library(tidyverse) # For data manipulation and visualization

# Load the dataset

df <- read\_excel("New China - ASEAN data (12.10.23).xlsx")

# Log-transform key variables

df <- df %>%

mutate(log\_OFALL = log(OFALL), log\_GDPpc = log(GDP\_per\_capita),

log\_Pop = log(Population), log\_OECD = log(OECD\_DAC),

log\_ADB\_Loans = log(ADB\_Loans))

**Step 2: Build the Null Model (Without Predictors)**

i begin by fitting a **null model** to verify the necessity of multilevel modeling, using the **Intraclass Correlation Coefficient (ICC)**. The ICC value is 0.13, greater than 0.1, meaning the responses are more similar within a cluster

# Null model (without predictors)

null\_model <- lmer(log\_OFALL ~ 1 + (1 | Country), data = df, REML = FALSE)

# Display summary and calculate ICC

summary(null\_model)

icc <- as.numeric(VarCorr(null\_model)$Country[1] /

(VarCorr(null\_model)$Country[1] + attr(VarCorr(null\_model), "sc")^2))

print(paste("ICC:", round(icc, 3))) # ICC confirms the necessity of multilevel modeling

**Step 3: Random Intercept Model (Only Level 1 Predictors)**

I fit a **random intercept model** using level 1 predictors, including **imports**, **exports**, and other economic variables.

# Random intercept model with level 1 predictors

trade\_int\_1 <- lmer(log\_OFALL ~ lag\_Imp.Percent.CN + lag\_Exp.Percent.CN +

lag\_UNSC + lag\_log\_GDPpc + lag\_log\_Pop +

lag\_Civil\_Conflict + lag\_Poly + lag\_log\_OECD +

lag\_log\_ADB\_Loans + (1 | Country), data = df, REML = FALSE)

# Model summary

summary(trade\_int\_1)

**Step 4: Add Level 2 Predictors (Territorial Disputes)**

Next, I include **SCS\_Border** and **SCS\_Features** to account for territorial disputes as level 2 predictors.

# Random intercept model with level 1 and level 2 predictors

trade\_int\_2 <- lmer(log\_OFALL ~ lag\_Imp.Percent.CN + lag\_Exp.Percent.CN +

lag\_UNSC + lag\_log\_GDPpc + lag\_log\_Pop +

lag\_Civil\_Conflict + lag\_Poly + lag\_log\_OECD +

lag\_log\_ADB\_Loans + SCS\_Border + SCS\_Features +

(1 | Country), data = df, REML = FALSE)

# Model summary

summary(trade\_int\_2)

**Step 5: Adding Random Effects for Year**

We also tested including **year** as a random effect to capture variations across time.

# Random intercept model with year as a random effect

trade\_int\_3 <- lmer(log\_OFALL ~ lag\_Imp.Percent.CN + lag\_Exp.Percent.CN +

lag\_UNSC + lag\_log\_GDPpc + lag\_log\_Pop +

lag\_Civil\_Conflict + lag\_Poly + lag\_log\_OECD +

lag\_log\_ADB\_Loans + SCS\_Border + SCS\_Features +

(1 | Country) + (1 | Year), data = df, REML = FALSE)

# Model summary

summary(trade\_int\_3)

**Step 6: Random Slopes (Addressing Singularity)**

Finally, we attempted to fit a model with **random slopes** for imports and exports but encountered **singularity issues**, which indicated overfitting.

# Random intercept and slope model (with singularity issues)

trade\_slop\_1 <- lmer(log\_OFALL ~ lag\_Imp.Percent.CN + lag\_Exp.Percent.CN +

lag\_UNSC + lag\_log\_GDPpc + lag\_log\_Pop +

lag\_Civil\_Conflict + lag\_Poly + lag\_log\_OECD +

lag\_log\_ADB\_Loans + (1 + lag\_Imp.Percent.CN +

lag\_Exp.Percent.CN | Country), data = df, REML = FALSE)

# Check for singularity

isSingular(trade\_slop\_1)

**Model Comparison**

We compare the models using **ANOVA** to identify the best-fitting model. The **random intercept model with level 1 predictors** (Model 1) proves to be superior in terms of parsimony and diagnostic performance.

# Compare models using ANOVA

anova(trade\_int\_1, trade\_int\_2)

anova(trade\_int\_1, trade\_int\_3)

**Descriptive analysis**

**Figure 1: COF Distributions Across Southeast Asia (2000-2021)**

**Key Insight**: Countries like **Indonesia**, **Laos**, **Malaysia**, and the **Philippines** experienced significant increases in COF from 2015 onwards, particularly during periods of heightened South China Sea tensions.

Table 1: The Regression Results of Imports and Exports on COF Allocations

**Key Insight**: **Imports from China** significantly influence COF allocations (p < 0.05), supporting **H1(a)**, while **exports** do not significantly impact COF, rejecting **H1(b)**. For every 1% increase in the proportion of imports from China in the previous year, the expected log COF increases by 0.11 (Model 1).

Table 2: The Regression Results of Disputes and Resolution on COF Allocations

**Key Insight**: Territorial disputes and resolutions show mixed impacts, with peaceful resolutions negatively associated with COF allocations, rejecting **H2**.

Table 3: The Regression Results of BRI and AIIB Membership on COF Allocations

**Key Insight**: **BRI** and **AIIB memberships** do not have statistically significant effects on COF allocations, rejecting **H3**.

**Conclusion**

This project demonstrates that **economic interdependency**—particularly in terms of **imports** from China—plays a significant role in shaping China's COF allocations. However, **territorial disputes** and **institutional participation** show more nuanced and often insignificant effects. The **random intercept model** with **level 1 predictors** provided the best performance, balancing parsimony and robustness.