Predicting Banking Crises in Africa

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2022-12-21

Introduction

In the 1960s and 1970s, the large majority of African countries obtained independence from colonialism. Their economies prior were almost all exclusively export driven under colonial concepts of mercantilism. Unfortunately for many, due to a myriad of factors such as government corruption, lack of macroeconomic knowledge, lack of motivation to industrialize, or lack of foreign investment, their economies did not develop the manufacturing industry of other developing countries such as South Korea or China. One consequence is a GDP highly reliant on trade of specific natural resources, leaving a country particularly susceptible to currency and systemic risks. Sudden devaluation of a country's currency can lead it unable to pay back foreign debts. Likewise, a decrease in global demand could leave a country with overproduction issues, leaving citizens with insufficient money, causing problems of domestic debt, and possibly spark the start of hyperinflation.

These problems culminated in the 1980s and 1990s where many African countries experienced severe debt crises, with the economic shock having great impact on the financial sector. Many African countries experienced overall reduction of investment, domestic and foreign, decrease in trade credit, and insolvency of significant number of banks. It was not until the 2000s that the debt crisis subsided. This report will seek to predict the occurrence of a banking crisis by the occurrence of systemic crises, inflation rate, domestic and foreign debt default, and a few other macroeconomic variables.

Reviews of the literature relating to the banking crises of Africa generally agree that the individual factors that weaken banks, such as those outlined in the CAMELS rating system, play a significant role as they do in other parts of the world (Demirgüç-Kunt and Detragiache, 1998). Additionally, the unique macroeconomic situation and level of government involvement in many African countries also have a significant effect on whether a country had a financial crisis (Roland Daumont et al., 2004). This paper will primarily investigate the macroeconomic conditions and test its significance in the banking crises through the 1980-1999 timeframe for 13 African countries: Algeria, Angola, Central African Republic, Ivory Coast, Egypt, Kenya, Mauritius, Morocco, Nigeria, South Africa, Tunisia, Zambia and Zimbabwe.

Survey of the Literature

The first article I read was *Banking Crises in Emerging Economies: Origins and Policy Options* by Morris Goldstein and Philip Turner from 1996. This paper sought to find common significant causes of financial crises in developing countries, which are the countries most severely hit in terms of percent GDP by financial crises. This paper discussed negative externalities that can result from financial crises. Oftentimes, the "inflation tax" is when governments try to fund their deficits by placing unrealistic taxes on the public, an ineffective and harmful method to try to fix a financial crisis. These practices can have the effect of amplifying a crisis. To investigate some of the major factors at play here, Goldstein noted that macroeconomic volatility: external and domestic, play a key role in public and foreign confidence in banks. Volatile market conditions are often precursors to crisis. Sampling of Latin

American countries such as Venezuela and Ecuador, economies less diversified and heavily trade focused, faced large fluctuations in their terms of trade that turned against them and were in part a cause of their banking crises. This situation described is similar to the one I will be modeling, as many developing African countries have very little diversification in their economies. Additionally, Goldstein drew scatterplots illustrating trends from 1994-1996 for East Asian bankers being able to attract more investment, as well as being given longer maturities, than more unstable economies such as those in Latin America. The paper discusses far more topics than I can cover but in general it provided clear evidence that crises can repeat, or go on for several years in developing countries due to a circular pattern of volatility, credit risk, and shortsightedness of policymakers and bankers. Considering there are countries in my dataset with financial crises lasting many years, this is something worth modeling perhaps in the form of lags.

The next paper I read was *The Determinants of Banking Crises in Developing and Developed Countries* by Asli Demirguc-Kunt and Enrica Detragiache from 1998. They performed a more rigorous multivariate logit econometric model focusing specifically on the macroeconomic environment illustrated before by many including Goldstein. The paper also discusses the prevalence and dangers of systemic banking problems in many developing countries such as inadequate risk management, use of public funds to bailout insolvent banks, or weakening of managerial incentives. Their panel data includes all market economies for which data were available over the period 1980-94 excluding transitioning economies. They used countries that did not experience financial crises as controls, and found that low GDP growth, high real interest rates, and high inflation significantly increase the likelihood of systemic problems. Adverse terms of trade shocks, highlighted by Goldstein, were only concluded to have a weak impact on banking sector problems. They also noted the rate of depreciation of the exchange rate, which is also a column of data in my data set, did not have a significant effect. Their results were very robust within the scope of their model, testing 4 models and using a joint f test and AIC, and having around a 70% accuracy rate.

The last article I read, *Banking in Sub-Saharan Africa: What Went Wrong?* by Roland Daumont, Francoise Le Gall, and Francois Leroux, from 2004 specifically focused on the banking crises prevalent in Africa during the 1980s and 90s. Their data samples the period 1985-95 and looks at 10 countries: Benin, Cameroon, Cote d'Ivoire, Ghana, Guinea, Kenya, Nigeria, Senegal, Tanzania, and Uganda. Their paper sought to find significant factors behind these crises, as well as try to link those causes to past studies on crises around the world, such as Kunt and Detriagache's paper. The strength of their model was that their specific sample included government intervention as well as centralized and market economies. These variables had been too difficult to measure before, of which they will also be a source of error in my own report, as my data set does not have that data. The article also obtained data on individual banks and percentages of the banking systems that were affected during crises, as well as direct translations to loss of GDP. The specificity of the data looks at individual loan portfolios, their non-performing loans, capital and reserves, ratio of loans to deposits, real interest rate, and many more included in their panel data, with lineplots illustrating higher and lower levels between insolvent and solvent banks.

They ultimately concluded that several of their factors they tested in their sample reflect similar factors identified in past literature in other countries, notably Goldstein and Turner's. However, they also concluded that sub-Saharan Africa did have many endemic crises associated with heavy government intervention in addition to a lack of a "credit culture" that instills the view that repaying one's loans is important. I can see this being prevalent with how many debt defaults are in my data set. Perhaps their most important conclusion was that contagion did not actually play a significant role in propagating banking crises. Unlike areas like Southeast Asia, the bunching of crises in the 1980s and 1990s were common external shocks hitting many countries. The paper also then proceeds to counter a point made by Kunt and others before that a deposit insurance scheme contributed to these banking crises. I can not determine which I think is more accurate, probably this one due to its greater specificity and sampling data, but it did alert me that experts can create models that seek to solve similar issues and come out with different points.

Model

The final model will be a twoway linear model accounting for individual and time fixed effects using the plm package. Lags of specific variables will be tested using ADF and BIC tests. The reasoning for this comes from past literature where I know I am missing many variables and controls. Therefore, I am going to include both fixed effects. Lags will help account for some of the omitted variable bias too. Clustered standard errors will be used for all models as well. These steps will help improve the accuracy of my model knowing that individual countries can vary greatly from one other while still accounting for unobservable exogenous variables.

This is the general equation I will use with Y being banking crisis and is always 0 or 1. X represents my normal regressors, and D are my dummy explanatory variables minus one. There will be as many lags as deemed significant. Individual and Time fixed effects will be added and clustered standard errors will be calculated.

$$Y_{it} = \beta_1 * X_{it} + \beta_2 * X_{it-1} + \beta_3 * X_{2it} + \beta_4 * X_{2it-1} + ...\beta_k * X_{2it-k}$$

$$+\gamma_1 * D_1 + \gamma_{k-1} * D_{K-1} + IndividualEffects + TimeFixedEffects + u_{it}$$

Data

I used the data set on occurrence of banking crises in African countries from https://www.kaggle.com/datasets/chirin/africa-economic-banking-and-systemic-crisis-data, a subset from https://www.hbs.edu/behavioral-finance-and-financial-stability/data. The countries covered in the data are Algeria, Angola, Central African Republic, Ivory Coast, Egypt, Kenya, Mauritius, Morocco, Nigeria, South Africa, Tunisia, Zambia, and Zimbabwe. There are a total of 69 bank crises during this period, and 180 no crises, for a total sample size of 249.

The panel data covers these variables:

systemic_crisis: “0” means that no systemic crisis occurred in the year and “1” means that a systemic crisis occurred in the year;

exch_usd: The exchange rate of the country in relation to USD;

domestic_debt_in_default : “0” means that no domestic debt default occurred in the year and “1” means that a domestic debt default occurred in the year;

sovereign_external_debt_default: “0” means that no sovereign external debt default occurred in the year and “1” means that a sovereign external debt default occurred in the year;

gdp_weighted_default: The total debt in default ratio in relation to the GDP;

inflation_annual_cpi: The annual CPI Inflation rate;

independence: “0” means “no independence” and “1” means “independence”;

currency_crises: “0” means that no currency crisis occurred in the year and “1” means that a currency crisis occurred in the year;

inflation_crises: “0” means that no inflation crisis occurred in the year and “1” means that an inflation crisis occurred in the year.

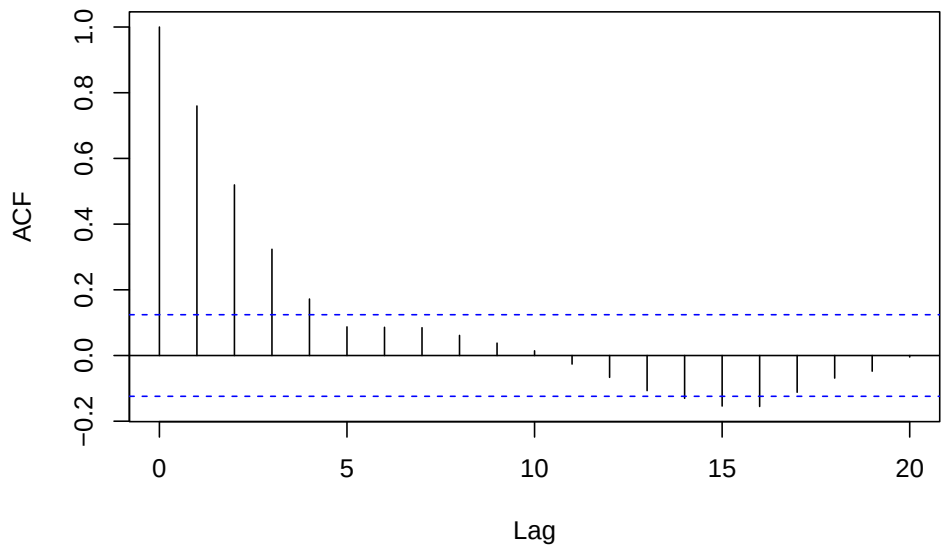
Empirical Application

I begin by creating the twoway fixed effects model. I also calculate clustered standard errors and add them to all models from now on.

```
Twoways effects Within Model

Note: Coefficient variance-covariance matrix supplied: vcov

Call:
plm(formula = bank_crisis_number ~ systemic_crisis + exch_usd +
    sovereign_external_debt_default + gdp_weighted_default +
    inflation_annual_cpi, data = ac.pd, effect = "twoways", model = "within")

Unbalanced Panel: n = 13, T = 10-20, N = 249

Residuals:
      Min.    1st Qu.     Median    3rd Qu.       Max.
-0.9545618 -0.0616155  0.0083204  0.0905084  0.9470263

Coefficients:
                                  Estimate  Std. Error  t-value  Pr(>|t|)
systemic_crisis                -8.3553e-01  7.4399e-02 -11.2303 < 2.2e-16 ***
exch_usd                        1.1801e-04  2.0548e-04   0.5743   0.56636
sovereign_external_debt_default 1.2809e-01  7.7337e-02   1.6562   0.09916 .
gdp_weighted_default           -5.9887e-01  3.2341e-01  -1.8518   0.06545 .
inflation_annual_cpi           -1.4189e-04  1.8373e-05  -7.7225 4.459e-13 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    33.365
Residual Sum of Squares: 11.903
R-Squared:      0.64324
Adj. R-Squared: 0.58266
F-statistic: 69.4468 on 5 and 12 DF, p-value: 1.9504e-08
```

I decide to test for multicollinearity as several of the variables would seem correlated in theory, such as domestic and sovereign debt defaults, or currency and inflation crises. Testing for multicollinearity actually reveals several aliased coefficients when trying to construct a simple linear model. The variables domestic_debt_in_default, currency_crises, inflation_crises, and independence have to be dropped in order to test multicollinearity with VIF.

Additionally, I had noted before from literature that possible autocorrelation may affect the model. After all, many of these crises span several years, so I should test for autocorrelation significance using the ADF and BIC test. I then added the relevant autocorrelations to my model. Shown below is the example for just systemic crises. The ADF test shows the data is stationary and the BIC test determines AR1 to be a better model than the AR4 model the ACF suggests.




```
Augmented Dickey-Fuller Test
alternative: stationary

Type 1: no drift no trend
     lag   ADF p.value
[1,]   0 -4.70    0.01
[2,]   1 -4.96    0.01
[3,]   2 -4.69    0.01
[4,]   3 -4.40    0.01
Type 2: with drift no trend
     lag   ADF p.value
[1,]   0 -5.58    0.01
[2,]   1 -5.99    0.01
[3,]   2 -5.81    0.01
[4,]   3 -5.60    0.01
Type 3: with drift and trend
     lag   ADF p.value
[1,]   0 -5.58    0.01
[2,]   1 -6.01    0.01
[3,]   2 -5.84    0.01
[4,]   3 -5.64    0.01
----
Note: in fact, p.value = 0.01 means p.value <= 0.01

         BIC
AR1 54.10618
AR4 71.65667

Twoways effects Within Model
```

```
Note: Coefficient variance-covariance matrix supplied: vcov

Call:
plm(formula = bank_crisis_number ~ +systemic_crisis + exch_usd +
    lag(systemic_crisis, 1) + +sovereign_external_debt_default +
    lag(sovereign_external_debt_default, 1) + gdp_weighted_default +
    inflation_annual_cpi + lag(inflation_annual_cpi, 1) + lag(inflation_annual_cpi,
    2) + lag(inflation_annual_cpi, 3), data = ac.pd, effect = "twoways",
    model = "within")

Unbalanced Panel: n = 13, T = 6-17, N = 206

Residuals:
      Min.    1st Qu.     Median    3rd Qu.       Max.
-0.9377758 -0.0586639  0.0092048  0.0827977  0.7394363

Coefficients:
                                       Estimate  Std. Error  t-value
systemic_crisis                      -9.7690e-01  3.2343e-02 -30.2038
exch_usd                             -6.5742e-05  1.9014e-04  -0.3458
lag(systemic_crisis, 1)               1.0576e-01  4.2518e-02   2.4874
sovereign_external_debt_default       1.2106e-01  4.4328e-02   2.7311
lag(sovereign_external_debt_default, 1)  1.5773e-01  6.9831e-02   2.2587
gdp_weighted_default                 -7.7993e-01  3.1282e-01  -2.4932
inflation_annual_cpi                 -6.0761e-05  2.4299e-05  -2.5006
lag(inflation_annual_cpi, 1)         -9.4973e-06  3.3905e-05  -0.2801
lag(inflation_annual_cpi, 2)         -1.7653e-04  1.1516e-05 -15.3300
lag(inflation_annual_cpi, 3)          1.3476e-04  4.7515e-05   2.8361
                                      Pr(>|t|)
systemic_crisis                      < 2.2e-16 ***
exch_usd                              0.729962
lag(systemic_crisis, 1)               0.013851 *
sovereign_external_debt_default       0.006990 **
lag(sovereign_external_debt_default, 1)  0.025197 *
gdp_weighted_default                  0.013634 *
inflation_annual_cpi                  0.013363 *
lag(inflation_annual_cpi, 1)          0.779735
lag(inflation_annual_cpi, 2)         < 2.2e-16 ***
lag(inflation_annual_cpi, 3)          0.005132 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    29.309
Residual Sum of Squares: 8.347
R-Squared:      0.71521
```

```
Adj. R-Squared: 0.6504
F-statistic: 758.883 on 10 and 12 DF, p-value: 3.2344e-15
```

This is the final plm model with all insignificant variables dropped.

```
Twoways effects Within Model

Note: Coefficient variance-covariance matrix supplied: vcov

Call:
plm(formula = bank_crisis_number ~ +systemic_crisis + lag(systemic_crisis,
    1) + sovereign_external_debt_default + lag(sovereign_external_debt_default,
    1) + gdp_weighted_default + inflation_annual_cpi + lag(inflation_annual_cpi,
    2) + lag(inflation_annual_cpi, 3), data = ac.pd, effect = "twoways",
    model = "within")

Unbalanced Panel: n = 13, T = 6-17, N = 206

Residuals:
     Min.   1st Qu.    Median   3rd Qu.      Max.
-0.935130 -0.060040  0.006803  0.086025  0.737748

Coefficients:
                                       Estimate  Std. Error  t-value
systemic_crisis                      -9.7651e-01  3.1678e-02 -30.8261
lag(systemic_crisis, 1)               1.0636e-01  4.2559e-02   2.4991
sovereign_external_debt_default       1.1741e-01  4.3238e-02   2.7155
lag(sovereign_external_debt_default, 1)  1.5842e-01  6.9408e-02   2.2825
gdp_weighted_default                 -7.7312e-01  3.1620e-01  -2.4450
inflation_annual_cpi                 -6.1620e-05  2.4896e-05  -2.4751
lag(inflation_annual_cpi, 2)         -1.7769e-04  1.5386e-05 -11.5485
lag(inflation_annual_cpi, 3)          1.3886e-04  3.5701e-05   3.8895
                                      Pr(>|t|)
systemic_crisis                      < 2.2e-16 ***
lag(systemic_crisis, 1)              0.0134061 *
sovereign_external_debt_default      0.0073056 **
lag(sovereign_external_debt_default, 1) 0.0237087 *
gdp_weighted_default                 0.0155118 *
inflation_annual_cpi                 0.0143065 *
lag(inflation_annual_cpi, 2)         < 2.2e-16 ***
lag(inflation_annual_cpi, 3)         0.0001442 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    29.309
Residual Sum of Squares: 8.3502
```

```
R-Squared:      0.7151
Adj. R-Squared: 0.65441
F-statistic: 339.591 on 8 and 12 DF, p-value: 6.0074e-13
```

Conclusion

The final significant regressors include whether a systemic crisis has occurred, if a systemic crisis occured last year, if a country defaulted on debt, the relation of total debt in default compared to the GDP, and annual inflation growth measured by CPI with lags 2 and 3. With this model, predict(FETELagmodel) predicted banking crises correctly for 53/69 of the banking crises that occurred in these countries from 1980-99. A 77% prediction accuracy with a joint f test significant at the 1% significance level.

This model is probably not very useful still, because while it provides evidence of macroeconomic variables written in great detail by Kunt and Detragiache, it has similar flaws in that I have not captured internal variables such as banking system structure, strength of individual banks, government intervention, and other more specific variable that could not possibly be all captured by the fixed effects.

Regarding interpretations of my coefficients. Systemic crisis has an estimate of -0.9765, which means that an African country that experiences a systemic crisis increases their probability of a banking crisis by 97 percentage points. The first lag of systemic crisis on the other hand, has an estimate of 0.106, possibly just the simple phenomenon that a country will not be in a crisis forever, and that eventually in the future the country will recover. Inflation and GDP weighted default is negative as expected; if debts make up a larger ratio of a country's GDP, then all the harder it is to restructure. The interesting estimate is sovereign default debt, which can be interpreted as if a country defaults on their sovereign debt, then their probability of a banking crisis actually decreases by 0.117 percentage points, and an additional 0.158 percentage points if they defaulted last year too. This is difficult to explain, as while there can be economic advantages of defaulting on debt, such as currency devaluation, the consequences of reduced investment and lending, stock market volatility and asset quality decrease all directly negative impact banks more. Additionally, I had already eliminated exchange rate as an insignificant regressor.

Overall, this model reflects for the most part the expected results for several macroeconomic variables and the their effect on the probability of a banking crisis. Perhaps with more data on other related variables such as elements of government interference and/or government ownership would help create even better models. Ultimately, I believe what this model best shows is the vulnerability of many African countries who struggled to develop manufacturing and diverse industries, leaving the country susceptible to systemic risks which can lead to a variety of social, economic, and political issues in the country, and ultimately a financial crisis.

References

Goldstein, Morris, and Philip Turner, 1996, "Banking Crises in Emerging Economies: Origins and Policy Options," BIS Economic Papers (October), No. 46 (Basel: Bank for International Settlements).

Demirgüç-Kunt, Asli, and Enrica Detriagache, 1998, "The Determinants of Banking Crisis in Developing and Developed Countries," Staff Papers, International Monetary Fund, Vol. 45 (March)

Daumont, Roland, Françoise Le Gall, and François Leroux, " Banking in Sub-Saharan Africa: What Went Wrong?" IMF Working Paper ## Appendix: All code for this report

```
knitr::opts_chunk$set(
    eval = TRUE,message   = FALSE, warning   = FALSE,   echo = FALSE, fig.align = "center",     comment =
)
```

```
library(ggplot2)
library(dplyr)
library(readr)
african_crises <- read_csv("african_crises.csv", show_col_types = FALSE)
data2 <- filter(african_crises)
data2 <- data2 %>%
  mutate(bank_crisis_number = ifelse(banking_crisis == "no_crisis", 1, ifelse(banking_crisis == "crisis",
data2 <- filter(data2, year > 1979 & year < 2000)
library(plm)
library(lmtest)

ac.pd <- pdata.frame(data2, index=c("country","year"),
                             drop.index=TRUE, row.names=TRUE)
pooled <- plm(bank_crisis_number~inflation_annual_cpi, data = ac.pd, model = "pooling")
# summary(pooled)

FEmodel = plm(bank_crisis_number~systemic_crisis+exch_usd+domestic_debt_in_default+sovereign_external_debt

FETEmodel <- plm(bank_crisis_number~systemic_crisis+exch_usd+sovereign_external_debt_default+gdp_weighted_

vcov<- sandwich::vcovHC(FEmodel, type = "HC1")
fit.robus <- lmtest::coeftest(FEmodel, vcov. = vcov)
# summary(FEmodel, vcov)

vcov<- sandwich::vcovHC(FETEmodel, type = "HC1")
fit.robus <- lmtest::coeftest(FETEmodel, vcov. = vcov)
summary(FETEmodel, vcov)
library(car)
#cor( data2[, c('domestic_debt_in_default', 'sovereign_external_debt_default', 'independence', 'systemic_c
FETELagmodel <- plm(bank_crisis_number~systemic_crisis+lag(systemic_crisis)+lag(systemic_crisis,2)+ lag(sy

vcov<- sandwich::vcovHC(FETELagmodel, type = "HC1")
fit.robus <- lmtest::coeftest(FETELagmodel, vcov. = vcov)

#summary(FETELagmodel, vcov)
acff2<-  acf(ac.pd$systemic_crisis, main = "ACF of systemic crisis",  na.action = na.omit, lag.max = 20)
library(aTSA)
adf.test((ac.pd$systemic_crisis), nlag = 4)

ar1 <- lm(ac.pd$systemic_crisis~ lag(ac.pd$systemic_crisis,1), data = ac.pd)
ar4 <- lm(ac.pd$systemic_crisis ~ lag(ac.pd$systemic_crisis) + lag(ac.pd$systemic_crisis, 2) + lag(ac.pd$s

bic <- data.frame(c(BIC(ar1), BIC(ar4)))
rownames(bic) = c("AR1","AR4")
colnames(bic) = c("BIC")
```

```
bic

FETELagmodel <- plm(bank_crisis_number~ +systemic_crisis +exch_usd +lag(systemic_crisis,1)  +  +sovereign_

# acff3<-  acf(ac.pd$inflation_annual_cpi, main = "ACF of AMZN returns",  na.action = na.omit, lag.max = 2
# adf.test((ac.pd$inflation_annual_cpi), nlag = 4)
ar1 <- lm(ac.pd$inflation_annual_cpi~ lag(ac.pd$inflation_annual_cpi,1), data = ac.pd)
#summary(ar1)

ar3 <- lm(ac.pd$inflation_annual_cpi ~ lag(ac.pd$inflation_annual_cpi) + lag(ac.pd$inflation_annual_cpi, 2
#summary(ar3)
bic <- data.frame(c(BIC(ar1), BIC(ar3)))
rownames(bic) = c("AR1", "AR3")
colnames(bic) = c("BIC")
#bic
vcov<- sandwich::vcovHC(FETELagmodel, type = "HC1")
fit.robus <- lmtest::coeftest(FETELagmodel, vcov. = vcov)

summary(FETELagmodel, vcov)
#data2$p <- predict(systemic_crisis, data2)
#ggplot(data2, aes(x = year, y = p, color = country))+
# geom_point()
FETELagmodel <- plm(bank_crisis_number~ +systemic_crisis +lag(systemic_crisis,1) +sovereign_external_debt_
vcov<- sandwich::vcovHC(FETELagmodel, type = "HC1")
fit.robus <- lmtest::coeftest(FETELagmodel, vcov. = vcov)

summary(FETELagmodel, vcov)
#predict(FETELagmodel)
```