# Econ History Assignment 2

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## Econ History Assignment 2

### Loading libraries

```
library(data.table)
library(fixest)
library(stargazer)
library(aod)
library(readxl)
library(countrycode)
library(pROC)
library(lpirfs)
```

### Importing data

```
jst = fread("../data/JSTdatasetR6.csv")
rec = fread("../data/RecessionDummies.csv")
bvx = fread("../data/bvx_crises_list.csv")
```

### Part A - Logit

Estimate a logit model with country fixed effects and with five lags of log changes in Money as a predictor for JST crises and document the results in table.

- Test for joint significance of five lags credit growth.
- Repeat with BVX crisis date
- Use 5-year change in the ratio of credit over GDP predictor

.

#### JST Crises

```r
# Create dependent variable and estimate model

jst[, tloans_real := tloans/cpi]
jst[, ln_tloans_real := log(tloans_real),]
jst[, ln_diff_tloans := ln_tloans_real - shift(ln_tloans_real, 1, type = "lag"), by = country]

logit_credit = glm(crisisJST ~
    shift(ln_diff_tloans, 1, type = "lag")
    + shift(ln_diff_tloans, 2, type = "lag")
    + shift(ln_diff_tloans, 3, type = "lag")
    + shift(ln_diff_tloans, 4, type = "lag")
    + shift(ln_diff_tloans, 5, type = "lag")
    + factor(country)
  ,family = binomial(link = "logit"),
  data = jst)

stargazer(logit_credit,
        type = "text",
        align = TRUE,
        omit = c("country"),
        dep.var.labels = c("Crisis (JST)"),
        covariate.labels = c("Log-change Real Credit - T-1",
                             "Log-change Real Credit - T-2",
                             "Log-change Real Credit - T-3",
                             "Log-change Real Credit - T-4",
                             "Log-change Real Credit - T-5"))
```

```
##
## =========================================================
##                                  Dependent variable:
##                              ---------------------------
##                                     Crisis (JST)
## ---------------------------------------------------------
## Log-change Real Credit - T-1            0.367
##                                        (1.372)
##
## Log-change Real Credit - T-2          6.742***
##                                        (1.224)
##
## Log-change Real Credit - T-3           -0.474
##                                        (1.051)
##
## Log-change Real Credit - T-4            0.007
##                                        (0.978)
##
## Log-change Real Credit - T-5            1.151
##                                        (1.101)
##
## Constant                             -4.697***
##                                        (0.725)
##
## ---------------------------------------------------------
## Observations                            2,333
```

```
## Log Likelihood                           -306.139
## Akaike Inf. Crit.                         658.278
## ==========================================================
## Note:                          *p<0.1; **p<0.05; ***p<0.01
```

The findings indicate that the log-change in real credit at T-2 is the only statistically significant predictor of a crisis in this model. Its effect is positive: an increase in credit in period t increases the likelihood of witnessing a crisis in t+2. In contrast, the other lagged variables do not show significant contributions to explaining the likelihood of a crisis.

We now test for the joint significance of the lag variables. A first attempt to challenge the joint significance could be a Wald test. The null hypothesis is that the five lags of credit growth are not jointly significant:

$$H_0 : \beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = 0$$

```
wald.test(
b = coef(logit_credit),  # Coefficients from the full model
Sigma = vcov(logit_credit),  # Variance-covariance matrix of coefficients
Terms = 2:6 # Indices of lagged predictors in the model
  )
```

```
## Wald test:
## ----------
##
## Chi-squared test:
## X2 = 35.8, df = 5, P(> X2) = 1e-06
```

Complementary, we can test joint significance with the likelihood ratio chi-square test. This tests consists of comparing the full model with a restricted model without the variables we want to test for. Let's first estimate the restricted model.

```
  # Test for joint significance of five lags credit growth.
  # We run a restricted model which excludes the five lags of credit growth
restricted_model <- glm(
  formula = crisisJST ~ factor(country),
  data = jst,
  family = binomial(link = "logit")
)
```

Now let's run the LR test.

```
lr_stat <- 2 * (logLik(logit_credit) - logLik(restricted_model))
df <- 5
p_value <- pchisq(lr_stat, df = df, lower.tail = FALSE)
cat("Likelihood Ratio Statistic:", lr_stat, "\n")
```

```
## Likelihood Ratio Statistic: 141.4017
```

```
cat("Degrees of Freedom:", df, "\n")
```

```
## Degrees of Freedom: 5
```

```r
cat("P-value:", p_value, "\n")
```

```
## P-value: 9.009139e-29
```

In both cases the p-value is close to 0, which means that we can reject the null hypothesis. Therefore, the five lags jointly contribute significantly to predicting the crisis variable.

```r
# We merge
setnames(bvx, "countrycode", "iso")
bvx = bvx[, country := NULL]
jst = merge(jst, bvx, all.x = TRUE, by = c("iso", "year"))

# We regress

logit_bvx = glm(bvx_crisis ~
      shift(ln_diff_tloans, 1, type = "lag")
      + shift(ln_diff_tloans, 2, type = "lag")
      + shift(ln_diff_tloans, 3, type = "lag")
      + shift(ln_diff_tloans, 4, type = "lag")
      + shift(ln_diff_tloans, 5, type = "lag")
      + factor(country)
    ,family = binomial(link = "logit"),
    data = jst)

stargazer(logit_bvx,
          type = "text",
          align = TRUE,
          omit = c("country"),
          dep.var.labels = c("BVX Crisis"),
          covariate.labels = c("Log-change Real Credit - T-1",
                               "Log-change Real Credit - T-2",
                               "Log-change Real Credit - T-3",
                               "Log-change Real Credit - T-4",
                               "Log-change Real Credit - T-5"))
```

**BVX Crises**

```
##
## ==========================================================
##                                  Dependent variable:
##                              ---------------------------
##                                      BVX Crisis
## ----------------------------------------------------------
## Log-change Real Credit - T-1           -0.476
##                                        (0.991)
##
## Log-change Real Credit - T-2          5.284***
##                                        (1.104)
##
```

```
## Log-change Real Credit - T-3           -0.786
##                                        (0.913)
##
## Log-change Real Credit - T-4           -0.046
##                                        (0.890)
##
## Log-change Real Credit - T-5           2.210**
##                                        (0.933)
##
## Constant                              -4.170***
##                                        (0.592)
##
## --------------------------------------------------------
## Observations                            2,334
## Log Likelihood                        -393.046
## Akaike Inf. Crit.                      832.092
## ========================================================
## Note:                        *p<0.1; **p<0.05; ***p<0.01
```

Similar to what was found with JST crisis, the outputs of the regression indicate that the log-change in real credit at T-2 is a statistically significant predictor of a crisis. Once again, its effect is positive: an increase in credit in period t increases the likelihood of witnessing a crisis in t+2. However, using BVX crisis we find that log change in real credit at T-5 is also a statistically significant predictor of a crisis. It's effect is however weaker as the coefficient is lower.

```
wald.test(
  b = coef(logit_bvx),  # Coefficients from the full model
  Sigma = vcov(logit_bvx),  # Variance-covariance matrix of coefficients
  Terms = 2:6 # Indices of lagged predictors in the model
)
```

```
## Wald test:
## ----------
##
## Chi-squared test:
## X2 = 30.1, df = 5, P(> X2) = 1.4e-05
```

Conclusion: We reject the null hypothesis, variables are jointly significant and able to predict the output variable. Hence, we get approximately the same result between BVX and JST crises classifications.

**GDP Ratio** Used 5-year change in the ratio of credit over GDP as a predictor

```
jst[, `:=` (gdp_real = gdp/cpi), by = c("country")]
jst[, creditgdp := tloans_real/gdp_real, by = c("country")]
jst[, creditgdpchange := creditgdp - shift(creditgdp, 5, type = "lag")]

logit_gdp = glm(crisisJST ~
                creditgdpchange
                + factor(country)
                ,family = binomial(link = "logit"),
                data = jst)
```

```r
stargazer(logit_gdp,
          type = "text",
          align = TRUE,
          omit = c("country"),
        dep.var.labels = c("Crisis (JST)"),
        covariate.labels = c("Credit-to-GDP 5Y Change"))
```

```
##
## ===================================================
##                            Dependent variable:
##                        ---------------------------
##                               Crisis (JST)
## ---------------------------------------------------
## Credit-to-GDP 5Y Change         3.413***
##                                  (0.866)
##
## Constant                        -4.483***
##                                  (0.718)
##
## ---------------------------------------------------
## Observations                      2,348
## Log Likelihood                  -318.110
## Akaike Inf. Crit.                674.221
## ===================================================
## Note:                  *p<0.1; **p<0.05; ***p<0.01
```

### Model estimation

**ROC test - Logit Model predictions using Real Credit Change** Compare in-sample and out of sample ROC, estimating the model until 1984 and predicting crisis for post-1984 years.

```r
# we split data in two
pre1984 = jst[year <= 1984,]
post1984 = jst[year > 1984,]

# we test on our pre-1984 data
logit_1984 = glm(crisisJST ~
      shift(ln_diff_tloans, 1, type = "lag")
      + shift(ln_diff_tloans, 2, type = "lag")
      + shift(ln_diff_tloans, 3, type = "lag")
      + shift(ln_diff_tloans, 4, type = "lag")
      + shift(ln_diff_tloans, 5, type = "lag")
      + country
    ,family = binomial(link = "logit"),
    data = pre1984)

# Predict probabilities for training data (in-sample)
pre1984$predicted_prob <- predict(logit_1984, pre1984, type = "response")

# Predict probabilities for testing data (out-of-sample)
post1984$predicted_prob <- predict(logit_1984, post1984, type = "response")
```

```r
# Compute ROC curve for in-sample data
roc_in_sample <- roc(pre1984$crisisJST, pre1984$predicted_prob)
```

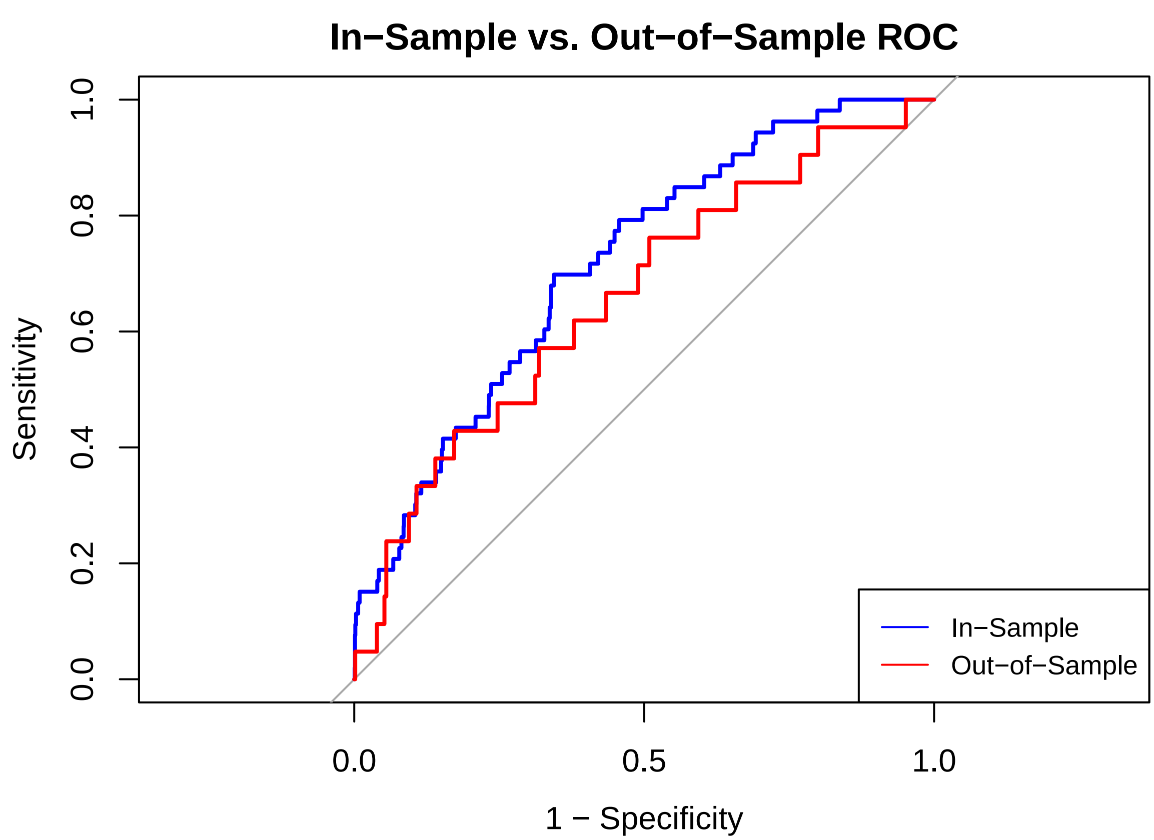
```
## Setting levels: control = 0, case = 1
```

```
## Setting direction: controls < cases
```

```r
# Compute ROC curve for out-of-sample data
roc_out_sample <- roc(post1984$crisisJST, post1984$predicted_prob)
```

```
## Setting levels: control = 0, case = 1
## Setting direction: controls < cases
```

```r
# Plot ROC curves
plot(roc_in_sample, col = "blue", main = "In-Sample vs. Out-of-Sample ROC", legacy.axes = TRUE)
plot(roc_out_sample, col = "red", add = TRUE)

# Add legend
legend("bottomright", legend = c("In-Sample", "Out-of-Sample"),
       col = c("blue", "red"), lty = 1, cex = 0.8)
```




```r
# Print AUC values
cat("In-Sample AUC: ", auc(roc_in_sample), "\n")
```

```
## In-Sample AUC:  0.7161041
```

```
cat("Out-of-Sample AUC: ", auc(roc_out_sample), "\n")
```

```
## Out-of-Sample AUC:  0.6581494
```

As we can judge from the Area Under the ROC (AUROC/AUC), the logit model using real credit as a predictor for financial crises has satisfactory in-sample performances (In-Sample AUC: 0.7161041), which drop slightly below the usual satisfactory threshold of 0.7 when predicting out of sample (Out-of-Sample AUC: 0.6581494). Further adjustments and variables might be needed to have a model with better predictive power.

**Money as predictor** Compare the baseline model to a logit model with money as a predictor.

```
jst[, money_real := money/cpi]
jst[, ln_money_real := log(money_real),]
jst[, ln_diff_money_real := ln_money_real - shift(ln_money_real, 1, type = "lag"), by = country]

logit_money = glm(crisisJST ~
      shift(ln_diff_money_real, 1, type = "lag")
      + shift(ln_diff_money_real, 2, type = "lag")
      + shift(ln_diff_money_real, 3, type = "lag")
      + shift(ln_diff_money_real, 4, type = "lag")
      + shift(ln_diff_money_real, 5, type = "lag")
      + factor(country)
    ,family = binomial(link = "logit"),
    data = jst)

stargazer(logit_money,
          type = "text",
          align = TRUE,
          omit = c("country"),
        dep.var.labels = c("Crisis (JST)"),
        covariate.labels = c("Log-change Money - T-1",
                             "Log-change Money - T-2",
                             "Log-change Money - T-3",
                             "Log-change Money - T-4",
                             "Log-change Money - T-5"))
```

```
##
## ===================================================
##                            Dependent variable:
##                        ----------------------------
##                               Crisis (JST)
## ---------------------------------------------------
## Log-change Money - T-1           1.841
##                                 (1.728)
##
## Log-change Money - T-2          4.241**
##                                 (1.702)
##
## Log-change Money - T-3          -0.692
```

```
##                                 (1.623)
##
## Log-change Money - T-4           2.127
##                                 (1.726)
##
## Log-change Money - T-5           1.703
##                                 (1.544)
##
## Constant                       -4.696***
##                                 (0.728)
##
## ---------------------------------------------------
## Observations                     2,399
## Log Likelihood                 -329.416
## Akaike Inf. Crit.               704.833
## ===================================================
## Note:                  *p<0.1; **p<0.05; ***p<0.01
```

In this model with money, the output of the regression indicates that, among all lagged independent variables, only the change in money at period t-2 increases the likelihood of witnessing a crisis in t significantly.

```r
jst[, diff_debtgdp := debtgdp - shift(debtgdp, 1, type = "lag"), by = c("country")]

logit_gdp = glm(crisisJST ~
      shift(diff_debtgdp, 1, type = "lag")
      + shift(diff_debtgdp, 2, type = "lag")
      + shift(diff_debtgdp, 3, type = "lag")
      + shift(diff_debtgdp, 4, type = "lag")
      + shift(diff_debtgdp, 5, type = "lag")
      + factor(country)
    ,family = binomial(link = "logit"),
    data = jst)

stargazer(logit_gdp,
          type = "text",
          align = TRUE,
          omit = c("country"),
        dep.var.labels = c("Crisis (JST)"),
        covariate.labels = c("Debt-to-GDP - T-1",
                             "Debt-to-GDP - T-2",
                             "Debt-to-GDP - T-3",
                             "Debt-to-GDP - T-4",
                             "Debt-to-GDP - T-5"))
```

**Public debt as predictor**

```
##
## ==============================================
##                      Dependent variable:
##                  ---------------------------
##                         Crisis (JST)
```

```
## ---------------------------------------------
## Debt-to-GDP - T-1          -1.254
##                            (1.978)
##
## Debt-to-GDP - T-2           0.280
##                            (2.278)
##
## Debt-to-GDP - T-3           1.104
##                            (2.223)
##
## Debt-to-GDP - T-4          -4.237**
##                            (1.777)
##
## Debt-to-GDP - T-5          -0.310
##                            (1.961)
##
## Constant                   -4.280***
##                            (0.712)
##
## ---------------------------------------------
## Observations                2,328
## Log Likelihood             -323.048
## Akaike Inf. Crit.           692.096
## =============================================
## Note:             *p<0.1; **p<0.05; ***p<0.01
```

In this model using lagged debt to gdp as a predictor of a crisis we unexpectedly find a significant negative coefficient for the log-change in real credit at T-4, indicating that an increase in debt to gdp in t-4 decrease the likelihood of witnessing a crisis in period t.

#### ROC tests - Models using Money and Debt-to-GDP ratio

We split again the data before and after 1984 to obtain our ROC test with the newly created variables.

```r
pre1984 = jst[year <= 1984,]
post1984 = jst[year >= 1984,]
```

```r
logit_1984 = glm(crisisJST ~
      shift(ln_diff_money_real, 1, type = "lag")
      + shift(ln_diff_money_real, 2, type = "lag")
      + shift(ln_diff_money_real, 3, type = "lag")
      + shift(ln_diff_money_real, 4, type = "lag")
      + shift(ln_diff_money_real, 5, type = "lag")
      + country
    ,family = binomial(link = "logit"),
    data = pre1984)

# Predict probabilities for training data (in-sample)
pre1984$predicted_prob <- predict(logit_1984, pre1984, type = "response")
```

```r
# Predict probabilities for testing data (out-of-sample)
post1984$predicted_prob <- predict(logit_1984, post1984, type = "response")

# Compute ROC curve for in-sample data
roc_in_sample <- roc(pre1984$crisisJST, pre1984$predicted_prob)
```

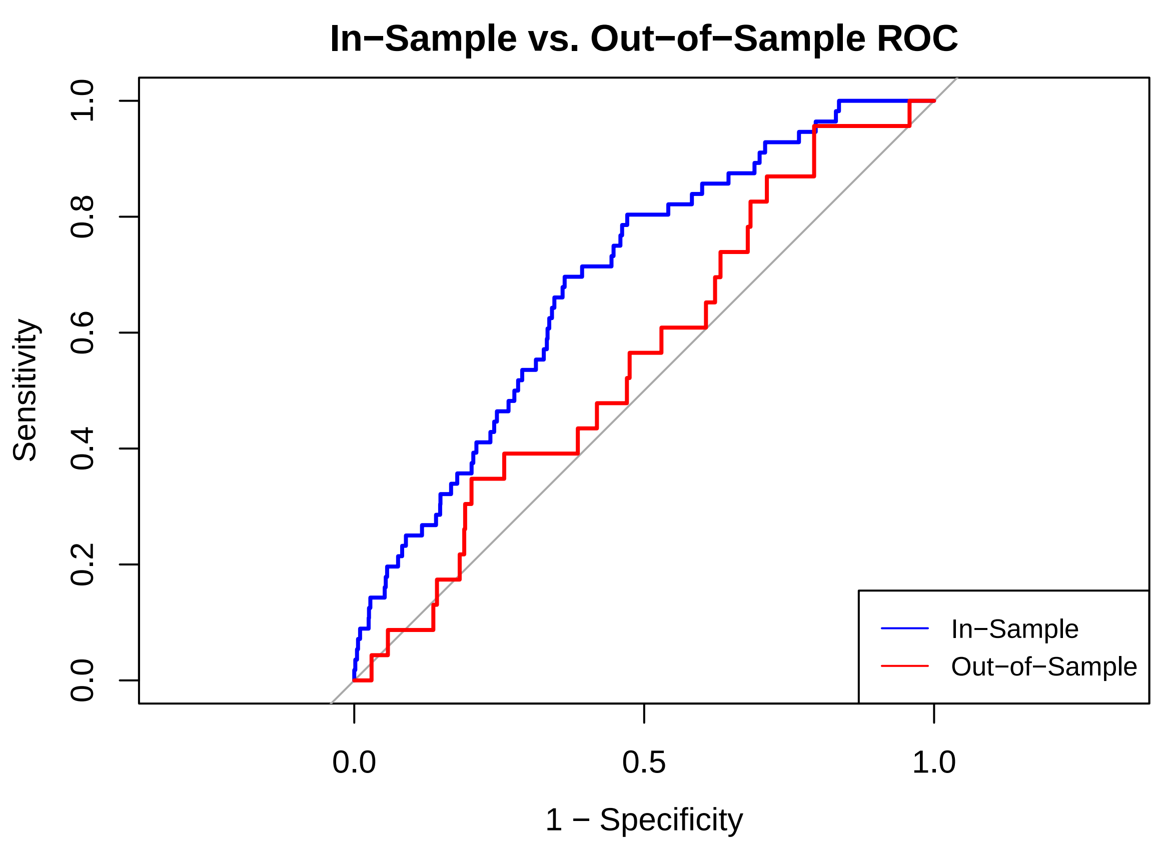
**Money**

```
## Setting levels: control = 0, case = 1

## Setting direction: controls < cases
```

```r
# Compute ROC curve for out-of-sample data
roc_out_sample <- roc(post1984$crisisJST, post1984$predicted_prob)
```

```
## Setting levels: control = 0, case = 1
## Setting direction: controls < cases
```

```r
# Plot ROC curves
plot(roc_in_sample, col = "blue", main = "In-Sample vs. Out-of-Sample ROC", legacy.axes = TRUE)
plot(roc_out_sample, col = "red", add = TRUE)

# Add legend
legend("bottomright", legend = c("In-Sample", "Out-of-Sample"),
       col = c("blue", "red"), lty = 1, cex = 0.8)
```



```r
# Print AUC values
cat("In-Sample AUC: ", auc(roc_in_sample), "\n")
```

```
## In-Sample AUC:  0.6912874
```

```r
cat("Out-of-Sample AUC: ", auc(roc_out_sample), "\n")
```

```
## Out-of-Sample AUC:  0.5588115
```

Similarly to the first model, the logit model using log-change in money as a predictor for financial crises has satisfactory in-sample performances (In-Sample AUC: 0.6912874), but has worse performances than the model using change in real credit when predicting out of sample (Out-of-Sample AUC: 0.5588115). We would therefore prefer to adopt real credit as a possible predictor.

```r
logit_1984 = glm(crisisJST ~
      shift(diff_debtgdp, 1, type = "lag")
      + shift(diff_debtgdp, 2, type = "lag")
      + shift(diff_debtgdp, 3, type = "lag")
      + shift(diff_debtgdp, 4, type = "lag")
      + shift(diff_debtgdp, 5, type = "lag")
      + country
    ,family = binomial(link = "logit"),
    data = pre1984)

# Predict probabilities for training data (in-sample)
pre1984$predicted_prob <- predict(logit_1984, pre1984, type = "response")

# Predict probabilities for testing data (out-of-sample)
post1984$predicted_prob <- predict(logit_1984, post1984, type = "response")

# Compute ROC curve for in-sample data
roc_in_sample <- roc(pre1984$crisisJST, pre1984$predicted_prob)
```

**Debt-to-GDP**

```
## Setting levels: control = 0, case = 1
```

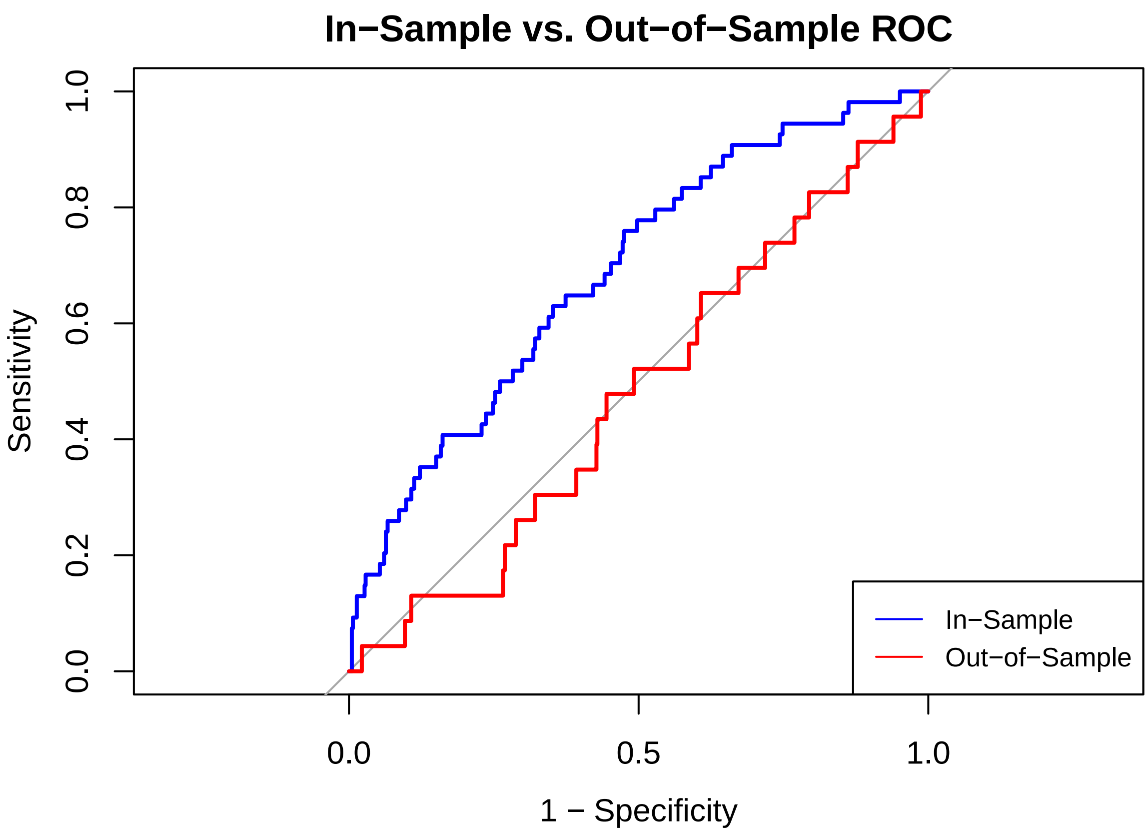
```
## Setting direction: controls < cases
```

```r
# Compute ROC curve for out-of-sample data
roc_out_sample <- roc(post1984$crisisJST, post1984$predicted_prob)
```

```
## Setting levels: control = 0, case = 1
```

```
## Setting direction: controls > cases
```

```r
# Plot ROC curves
plot(roc_in_sample, col = "blue", main = "In-Sample vs. Out-of-Sample ROC", legacy.axes = TRUE)
plot(roc_out_sample, col = "red", add = TRUE)

# Add legend
legend("bottomright", legend = c("In-Sample", "Out-of-Sample"),
       col = c("blue", "red"), lty = 1, cex = 0.8)
```




```r
# Print AUC values
cat("In-Sample AUC: ", auc(roc_in_sample), "\n")
```

```
## In-Sample AUC:  0.6879278
```

```r
cat("Out-of-Sample AUC: ", auc(roc_out_sample), "\n")
```

```
## Out-of-Sample AUC:  0.4794992
```

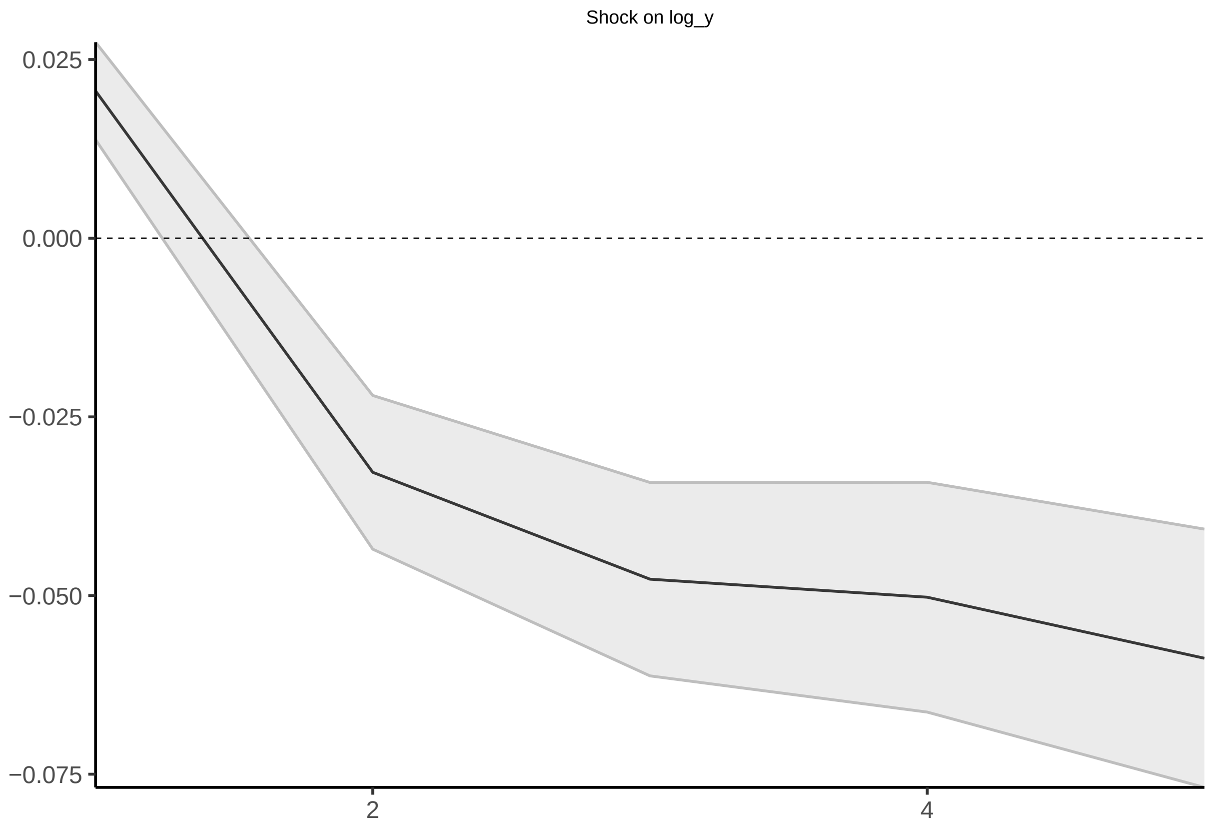
Analogous considerations apply to the model exploiting the Debt-to-GDP ratio, as it performs worse than both the previous models in sample and it is particularly unsatisfactory out of sample, showing very poor predictive power (Out-of-Sample AUC: 0.4794992).

## Part B - Linear projections

```
jst = merge(jst, rec, by = c("year", "iso"))
jst[, log_y := log(rgdpbarro)]

lp_reg = jst[, .(iso, year, log_y, N, `F`)]
lp_reg[, N := ifelse(is.na(N), 0, N)]
lp_reg[, `F` := ifelse(is.na(`F`), 0, `F`)]
```

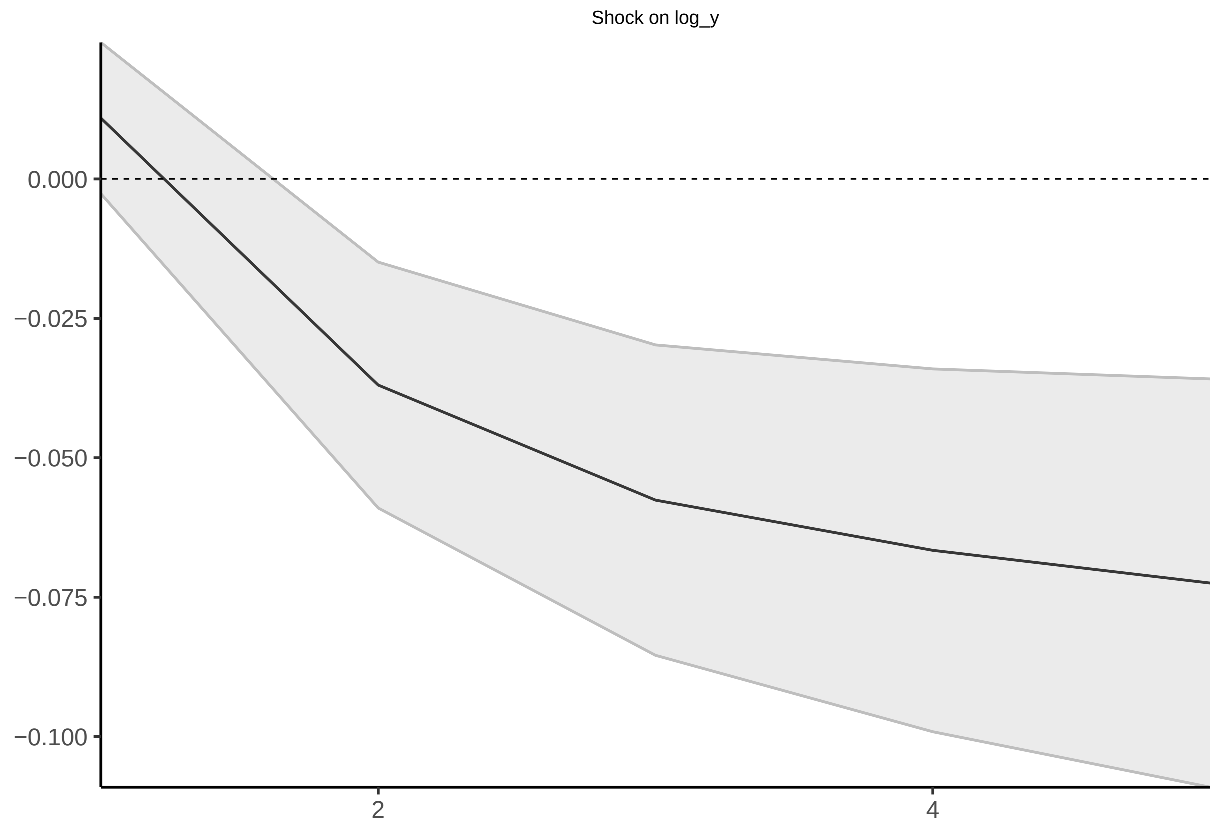
### Normal Recessions

```
lp_normal <- lp_lin_panel(
  data_set = lp_reg,
  endog_data = "log_y",       # Dependent variable
  cumul_mult = TRUE,          # Cumulative multipliers
  shock = "N",                # Normal recession
  diff_shock = FALSE,         # No differencing of shocks
  c_fd_exog_data = "F",
  panel_model = "within",     # Fixed effects model
  confint = 1.96,             # 95% confidence interval
  hor = 5                     # Horizons: 1 to 5 years
)

# Plot impulse response functions (IRFs)
plot(lp_normal)
```




**Financial Recessions**

```
lp_normal <- lp_lin_panel(
  data_set = lp_reg,
  endog_data = "log_y",       # Dependent variable
  cumul_mult = TRUE,          # Cumulative multipliers
  shock = "F",                # Normal recession
  diff_shock = FALSE,         # No differencing of shocks
  c_fd_exog_data = "N",
  panel_model = "within",     # Fixed effects model
  confint = 1.96,             # 95% confidence interval
  hor = 5                     # Horizons: 1 to 5 years
)

# Plot impulse response functions (IRFs)
plot(lp_normal)
```




The graphs reveal key differences in the economic costs of normal and financial recessions over a five-year horizon, with no evidence of recovery in either case. Both types of recessions exhibit a similar initial impact, with GDP per capita dropping sharply at year 1. However, their paths diverge slightly in the following years. In normal recessions, the GDP losses after year 1 remain consistently around -5% to -6% throughout the horizon. In financial recessions, the losses deepen gradually, reaching approximately -7% by year 5. The absence of recovery in both graphs highlights the persistent nature of the economic damage caused by recessions, with financial recessions appearing more costly due to their steadily worsening impact. Overall, the results indicate that neither type of recession allows for meaningful recovery within five years, with financial recessions causing slightly greater and more prolonged economic damage.