

Homework Assignment 4

Data Analysis & Statistics, Winter 2024/25

Lecturer: Dario Paape

Group Members:

Daniel Lösel

Martín E. Iribarren

1. Setup and Data Preparation

Loading Libraries

```
library(ggplot2)
library(dplyr)
```

```
##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##   filter, lag

## The following objects are masked from 'package:base':
##
##   intersect, setdiff, setequal, union
```

```
library(lme4)
```

```
## Loading required package: Matrix
```

```
library(readr)
library(tidyr)
```

```
##
## Attaching package: 'tidyr'

## The following objects are masked from 'package:Matrix':
##
##   expand, pack, unpack
```

```
library(tidyverse)
```

```
## -- Attaching core tidyverse packages ----- tidyverse 2.0.0 --
## v forcats   1.0.0      v stringr   1.5.1
## v lubridate 1.9.3      v tibble   3.2.1
## v purrr     1.0.2

## -- Conflicts ----- tidyverse_conflicts() --
## x tidyr::expand() masks Matrix::expand()
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
## x tidyr::pack()   masks Matrix::pack()
## x tidyr::unpack() masks Matrix::unpack()
## i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts
```

```
library(here)
```

```
## here() starts at C:/Users/emart/Backup/Osnabrück/Jahre/Zweites Jahr/3. Drittes Semest
```

Loading Dataset

```
dataset <- read.csv(here("data", "data_wdi", "data.csv"))
```

Data Pre-processing

```
#Select Columns
dataset <- dataset %>%
  select(-Country.Code, -Series.Code)

data_long <- dataset %>%
  pivot_longer(
    cols = starts_with("X"),
    names_to = "Year",
    values_to = "Value"
  ) %>%
  mutate(Year = gsub("X|\\.YR", "", Year))

data_clean <- data_long %>%
  filter(Series.Name %in% c("Gross fixed capital formation (% of GDP)",
    "General government final consumption expenditure (% of GDP)",
    "GDP (current US$)",
    "GDP growth (annual %)",
    "Inflation, GDP deflator (annual %)",
    "Control of Corruption: Estimate")) %>%

  pivot_wider(names_from = Series.Name, values_from = Value) %>%

  mutate(Year = gsub("[^0-9]", "", Year),
    Year = as.numeric(Year)) %>%

  rename(
    Total_Investment = "Gross fixed capital formation (% of GDP)",
    Government_Expenditure = "General government final consumption expenditure (% of GDP)",
    GDP = "GDP (current US$)",
    GDP_Growth = "GDP growth (annual %)",
    Inflation = "Inflation, GDP deflator (annual %)",
```

```
Control_of_Corruption = "Control of Corruption: Estimate"  
)
```

```
data_clean <- data_clean %>%  
  mutate(  
    Control_of_Corruption = ifelse(Control_of_Corruption == "..", 0.0, Control_of_Corruption),  
    across(c(Total_Investment, Government_Expenditure, GDP, Inflation, Control_of_Corruption),  
           ~ as.numeric(.)) %>%  
  ) %>%  
  mutate(GDP_Growth = as.numeric(GDP_Growth)) %>%  
  drop_na()
```

```
## Warning: There was 1 warning in 'mutate()'.  
## i In argument: 'across(...)'.  
## Caused by warning:  
## ! NAs introducidos por coerción
```

2. Exploratory Data Analysis

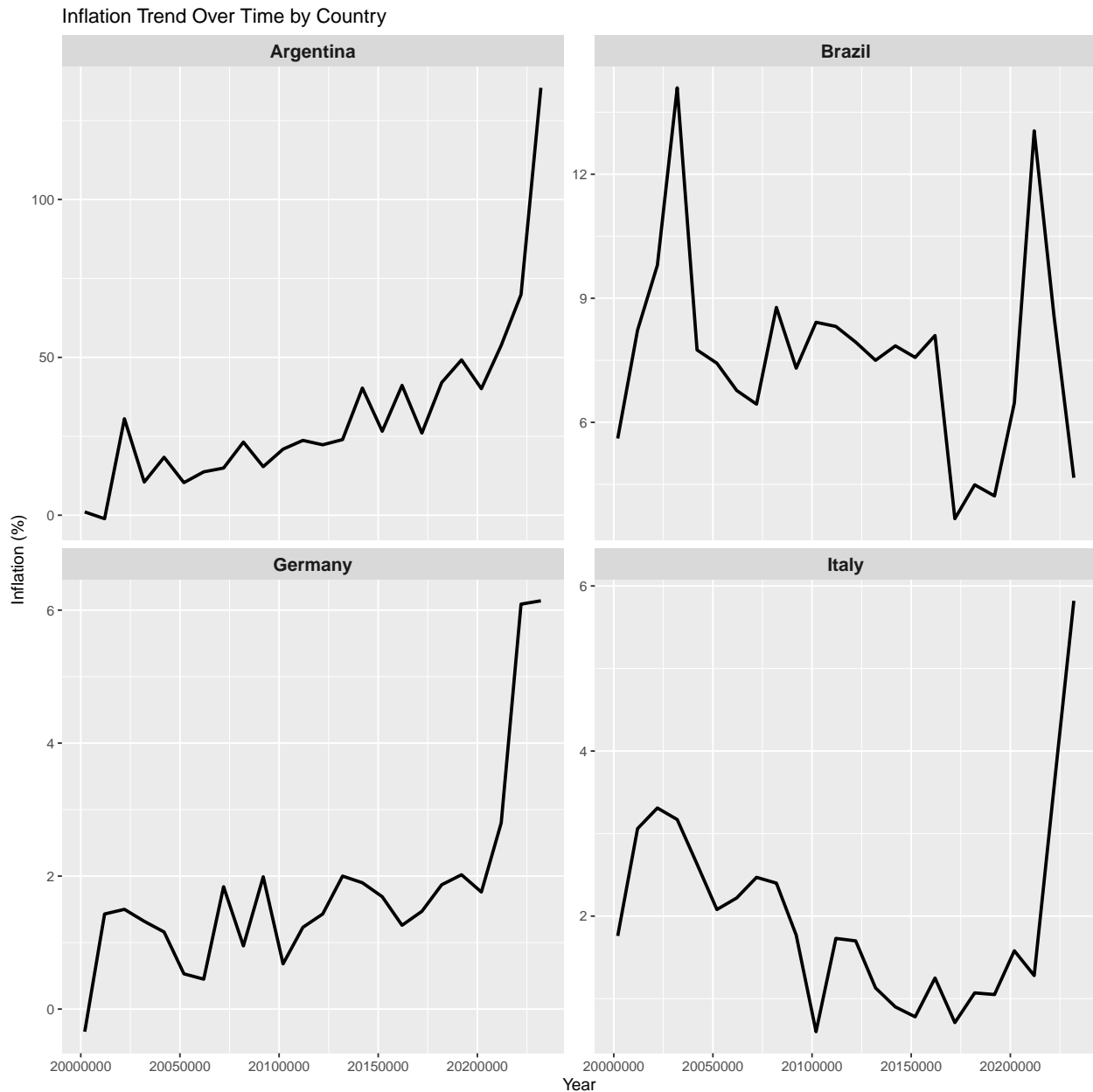
Inflation Distribution by Country

```
inflation_data <- data_clean %>%  
  filter(Country.Name %in% c("Germany", "Argentina", "Brazil", "Chile", "Italy")) %>%  
  select(Country.Name, Year, Inflation) %>%  
  group_by(Country.Name, Year) %>%  
  summarise(Inflation = mean(Inflation, na.rm = TRUE)) %>%  
  ungroup()
```

'summarise()' has grouped output by 'Country.Name'. You can override using the
'.groups' argument.

```
ggplot(inflation_data, aes(x = Year, y = Inflation)) +  
  geom_line(size = 1, color = "black") +  
  facet_wrap(~ Country.Name, scales = "free_y", ncol = 2) +  
  labs(title = "Inflation Trend Over Time by Country",  
       x = "Year",  
       y = "Inflation (%)") +  
  theme(  
    legend.position = "none",  
    strip.text = element_text(size = 12, face = "bold"), #  
  )
```

Warning: Using 'size' aesthetic for lines was deprecated in ggplot2 3.4.0.
i Please use 'linewidth' instead.
This warning is displayed once every 8 hours.
Call 'lifecycle::last_lifecycle_warnings()' to see where this warning was
generated.



Government Expenditure by Country (% of GDP)

```
investment_data <- data_clean %>%
  select(Country.Name, Year, Government_Expenditure) %>%
  group_by(Country.Name) %>%
  summarise(Average_Government_Expenditure = mean(Government_Expenditure, na.rm = TRUE))
  mutate(Average_Government_Expenditure = round(Average_Government_Expenditure, 2)) %>%
  arrange(desc(Average_Government_Expenditure)) %>%
  ungroup()
```

```
investment_data
```

```
## # A tibble: 20 x 2
##   Country.Name      Average_Government_Expenditure
##   <chr>              <dbl>
## 1 Netherlands      24.0
## 2 France            23.4
## 3 Saudi Arabia     23.3
## 4 United Kingdom   19.8
## 5 Germany           19.4
## 6 Australia         19.4
## 7 Brazil            19.2
## 8 Italy             19.2
## 9 Japan             19.1
## 10 Spain            18.8
## 11 Russian Federation 17.9
## 12 China            15.7
## 13 Argentina        15.1
## 14 United States    14.8
## 15 Korea, Rep.      14.7
## 16 Turkiye          13.6
## 17 Switzerland     11.3
## 18 Mexico           10.9
## 19 India            10.8
## 20 Indonesia        8.62
```

```
corruption_data <- data_clean %>%
  select(Country.Name, Year, Control_of_Corruption) %>%
  group_by(Country.Name) %>%
  summarise(Average_Control_of_Corruption = mean(Control_of_Corruption, na.rm = TRUE)) %>%
  mutate(Average_Control_of_Corruption = round(Average_Control_of_Corruption, 2)) %>%
  arrange(desc(Average_Control_of_Corruption)) %>%
  ungroup()

corruption_data
```

```
## # A tibble: 20 x 2
##   Country.Name      Average_Control_of_Corruption
##   <chr>              <dbl>
## 1 Switzerland      1.96
## 2 Netherlands      1.91
## 3 Australia         1.79
## 4 Germany           1.73
## 5 United Kingdom   1.69
## 6 Japan             1.34
## 7 United States    1.31
## 8 France            1.27
## 9 Spain             0.92
```

## 10 Korea, Rep.	0.5
## 11 Italy	0.31
## 12 Saudi Arabia	0.05
## 13 Turkiye	-0.16
## 14 Brazil	-0.21
## 15 China	-0.34
## 16 Argentina	-0.35
## 17 India	-0.38
## 18 Mexico	-0.58
## 19 Indonesia	-0.64
## 20 Russian Federation	-0.92

3. Hypothesis Testing

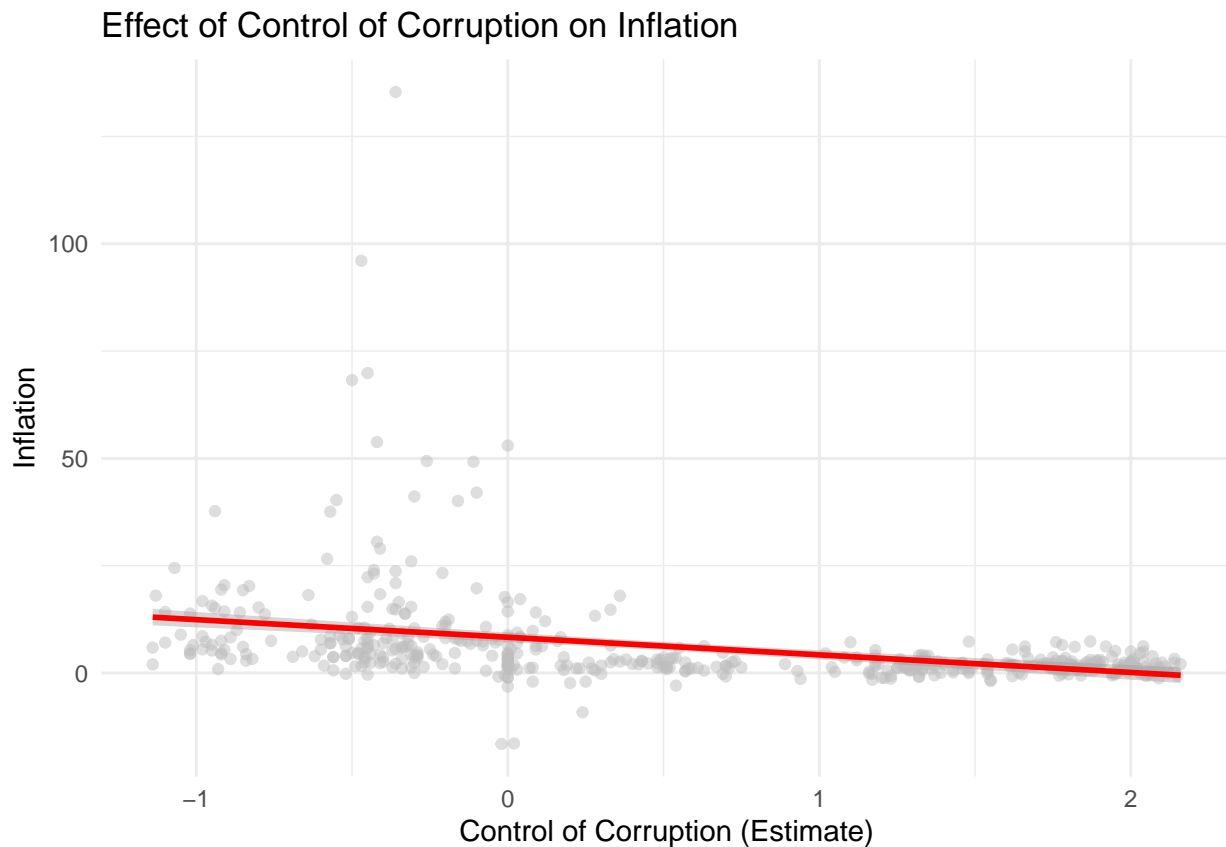
Hypothesis 1: Effect of Control of Corruption on Inflation

```
model_h1 <- lmer(Inflation ~ Control_of_Corruption + (1 | Country.Name),  
                 data = data_clean)  
summary(model_h1)
```

```
## Linear mixed model fit by REML ['lmerMod']  
## Formula: Inflation ~ Control_of_Corruption + (1 | Country.Name)  
## Data: data_clean  
##  
## REML criterion at convergence: 3495.4  
##  
## Scaled residuals:  
##      Min       1Q   Median       3Q      Max   
## -3.3502 -0.2161 -0.0378  0.1292 11.9185   
##  
## Random effects:  
## Groups      Name      Variance Std.Dev.  
## Country.Name (Intercept) 41.54     6.445  
## Residual                78.56     8.863  
## Number of obs: 479, groups: Country.Name, 20  
##  
## Fixed effects:  
##              Estimate Std. Error t value  
## (Intercept)         7.780     1.605   4.849  
## Control_of_Corruption -3.167     1.032  -3.068  
##  
## Correlation of Fixed Effects:  
##              (Intr)  
## Cntrl_f_Crr -0.360
```

```
ggplot(data_clean, aes(x = Control_of_Corruption, y = Inflation)) +  
  geom_point(alpha = 0.5, color = "gray") +  
  geom_smooth(method = "lm", aes(group = 1), color = "red", size = 1, se = TRUE) +  
  labs(title = "Effect of Control of Corruption on Inflation",  
        x = "Control of Corruption (Estimate)",  
        y = "Inflation") +  
  theme_minimal()
```

```
## 'geom_smooth()' using formula = 'y ~ x'
```



Interpretation Hypothesis 1:

The model indicates an average inflation of 7.7%, when the control of corruption is zero. The coefficient for `Control_of_Corruption` is -3.167 with a t-value of -3.068, meaning that for each unit increase in the control of corruption, inflation decreases by approximately 3.167%.

This negative relationship is statistically significant, supporting the hypothesis that better control of corruption is associated with lower inflation. However, as we will observe in the next models, the random effects show high variability across countries, with a variance of 41.54 and a standard deviation of 6.445.

Hypothesis 2: The effect of Government expenditure on GDP growth

```
model_h2 <- lmer(GDP_Growth ~ Government_Expenditure + (1 + Government_Expenditure || Country.Name)
summary(model_h2)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: GDP_Growth ~ Government_Expenditure + ((1 | Country.Name) + (0 +
##   Government_Expenditure | Country.Name))
## Data: data_clean
##
```

```
## REML criterion at convergence: 2440.4
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -5.1452 -0.3173  0.0675  0.4657  3.1625
##
## Random effects:
##   Groups             Name               Variance Std.Dev.
##   Country.Name      (Intercept)         7.666702  2.76888
##   Country.Name.1    Government_Expenditure 0.002129  0.04614
##   Residual                                8.349488  2.88955
## Number of obs: 479, groups: Country.Name, 20
##
## Fixed effects:
##              Estimate Std. Error t value
## (Intercept)      14.80679     1.54547   9.581
## Government_Expenditure -0.70876     0.08423  -8.414
##
## Correlation of Fixed Effects:
##              (Intr)
## Gvrnmnt_Exp -0.905
```

Interpretation Hypothesis 2:

The model indicates a significant negative relationship between government expenditure and GDP growth, with a coefficient of -0.70876 (t-value = -8.414). This suggests that higher government expenditure is associated with lower GDP growth. In terms of fixed effects, when there is zero government expenditure, the model predicts a baseline GDP growth of 14%. Additionally, the residuals appear reasonable, and indicate that the model fit might not be perfect for all countries, suggesting that some country-specific factors could influence the relationship between government expenditure and GDP growth.

Hypothesis 3: Effect of Total Investment on GDP

```
model_h3 <- lmer(GDP_Growth ~ Total_Investment + (1 | Country.Name),
                 data = data_clean)
summary(model_h3)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: GDP_Growth ~ Total_Investment + (1 | Country.Name)
##   Data: data_clean
##
## REML criterion at convergence: 2478.7
##
```

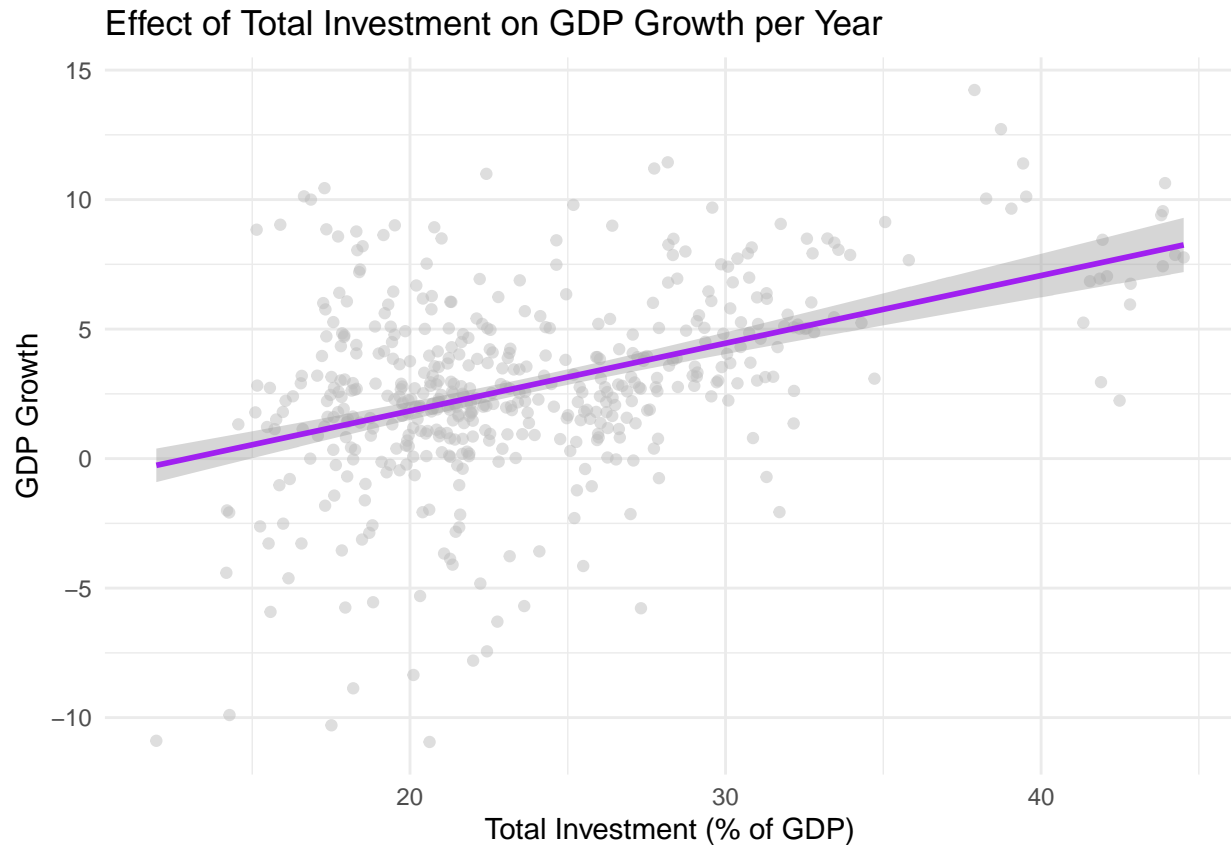
```
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -3.9789 -0.3498  0.0683  0.4547  2.7434
##
## Random effects:
##   Groups           Name      Variance Std.Dev.
##   Country.Name (Intercept) 1.090     1.044
##   Residual                9.729     3.119
## Number of obs: 479, groups: Country.Name, 20
##
## Fixed effects:
##              Estimate Std. Error t value
## (Intercept)   -2.70131    0.95450  -2.830
## Total_Investment  0.23245    0.03837   6.058
##
## Correlation of Fixed Effects:
##              (Intr)
## Ttl_Invstmn -0.958
```

```
gdp_investment <- data_clean %>%
  group_by(Country.Name, Year) %>%
  summarise(Total_Investment = mean(Total_Investment),
            GDP_Growth = mean(GDP_Growth))
```

```
## 'summarise()' has grouped output by 'Country.Name'. You can override using the
## '.groups' argument.
```

```
ggplot(gdp_investment, aes(x = Total_Investment, y = GDP_Growth)) +
  geom_point(alpha = 0.5, color = "gray") +
  geom_smooth(method = "lm", aes(group = 1), color = "purple", size = 1, se = TRUE) +
  labs(title = "Effect of Total Investment on GDP Growth per Year",
       x = "Total Investment (% of GDP)",
       y = "GDP Growth") +
  theme_minimal()
```

```
## 'geom_smooth()' using formula = 'y ~ x'
```



Interpretation Hypothesis 3: The model shows a positive correlation between total investment and GDP growth (coefficient of 0.23245, $t = 6.058$). The variability in the random effects suggests that some countries exhibit atypical behavior compared to the rest. This can be understood in light of the high negative correlation between the intercept and Total_Investment (-0.958), which could indicate differences in the initial growth levels between countries with varying investment levels.