Determining the effect of the Fiscal Multiplier on the Australian Economy during Recessionary/Non-Recessionary Periods (1959 - 2024)

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1. Introduction

The objective of this analysis is to evaluate the effect of the *Fiscal Multiplier* (M) on the Australian economy from 1959 to 2024. Using monthly GDP growth rate (ΔY_t) and government expenditure data (ΔG_t), the analysis estimates how changes in government spending impact GDP. Additionally, an indicator variable (R_t) is included to account for recessionary periods, defined as months experiencing negative GDP growth.

The relationship can be expressed as:

$$\Delta Y_t = \alpha + M \cdot \Delta G_t + \beta R_t + \epsilon_t$$

Where:
- ΔY_t: Change in GDP (growth rate) at time t.
- ΔG_t: Change in government expenditure at time t.
- M: Fiscal multiplier.
- R_t: Recession indicator ($R_t = 1$ if month t is recessionary, $R_t = 0$ otherwise).
- β: Coefficient for the recession indicator.
- ϵ_t: Error term capturing unexplained variations at time t.

2. Data Requirements

Variables to Collect

1. **Real GDP (Y):**
    - Use quarterly or annual GDP data, adjusted for inflation.
    - Look for Real GDP in constant prices to measure actual economic output.
2. **Government Spending (G):**
    - Government Final Consumption Expenditure: Spending on public services (e.g., healthcare, education, defense).
    - Government Investment (Gross Fixed Capital Formation): Spending on long-term assets like infrastructure.
    - If available, use Total Government Spending (combines consumption and investment).
3. **Inflation (Optional):**
    - Use the GDP deflator or Consumer Price Index (CPI) to adjust nominal values if only nominal data is available.

1. Data Sources for Australia

1. **Australian Bureau of Statistics (ABS):**
   - National Accounts:
     - Real GDP: National Accounts - Key Economic Indicators.

     - Government Final Consumption Expenditure.

     - Gross Fixed Capital Formation.

   - Look for time-series datasets in Excel or CSV format.
2. **Reserve Bank of Australia (RBA):**
   - Provides detailed economic indicators, including GDP and fiscal data.

2. Preparing the Data

Steps:

1. **Organize Variables:**
   - Ensure Y_t (GDP) and G_t (Government Spending) are aligned by time (e.g., quarterly or annual).

   - Use real values or adjust nominal data using inflation indices.
2. **Calculate Changes (ΔY_t and ΔG_t):**
   - Compute differences for each period:

$$\Delta Y_t = Y_t - Y_{t-1}, \quad \Delta G_t = G_t - G_{t-1}$$

3. **Normalize Changes (Optional):**
   - Divide changes by lagged GDP for scale:

$$\text{Normalized } \Delta G_t = \frac{\Delta G_t}{Y_{t-1}}$$

4. **Incorporate Recession Indicator:**
   - Add R_t, where $R_t = 1$ if GDP growth is negative in period t, and $R_t = 0$ otherwise.

3. Model Specification

Regression Setup:

Run a regression to estimate the multiplier:

$$\Delta Y_t = \alpha + M \cdot \Delta G_t + \beta R_t + \epsilon_t$$

Where:
- M: Fiscal multiplier (coefficient on ΔG_t).
- β: Coefficient for the recession indicator.
- α: Constant (intercept term).
- ϵ_t: Error term.

4. Interpretation

- **Multiplier $M > 1$:**
  Government spending leads to a larger proportional increase in GDP.
- **Multiplier $M < 1$:**
  Government spending has a smaller effect on GDP, possibly due to crowding out.
- **Multiplier $M < 0$:**
  Spending negatively affects GDP, suggesting inefficiencies or distortions.

5. Deliverables

1. **Dataset:**
   - Include columns: Date, Real GDP (Y_t), Government Spending (G_t), Recession Indicator (R_t), and computed changes (ΔY_t, ΔG_t).
2. **Graphical Analysis:**
   - Plot GDP and Government Spending over time.
   - Visualize ΔY_t vs. ΔG_t to see their relationship.
3. **Regression Output:**
   - Present the estimated M with confidence intervals.
   - Include R^2 and statistical significance.

3. Data loading and processing

We begin by first loading and cleaning the data.

```
# 1. Load data
url  <- "https://docs.google.com/spreadsheets/d/1ak0i7mCieYlg_-YO3u-5L5qg7FP2XrJNbxZOZthgt1U/edit?usp=sl
data <- read_sheet(url, sheet = "Sheet1")

data <- data %>% mutate(

  # Create CPI Index column indexed at 100
  cpi_index = 100 + `All Groups CPI`,

  # Create Real GDP column
  Real_GDP = (`Gross domestic product (Current prices, Millions)` *
                100)/cpi_index,

  # Calculate the Total Government Expenditure
  Total_Gov_Exp = `General government - National Final Consumption Expenditure (Millions)` +
    `General government - National Gross fixed capital formation (Millions)`,
  # Calculate the difference between current and lagged Real GDP and
  # Lagged Total Government Expenditure:
  diff_rgdp = Real_GDP - lag(Real_GDP),
  diff_tge = Total_Gov_Exp - lag(Total_Gov_Exp),

  # Percentage in Real GDP
  rgdp_perc_change = ((Real_GDP - lag(Real_GDP))/lag(Real_GDP)) * 100,

  # Create a new column called recession = 1 if recession, 0 otherwise
  recession = ifelse(rgdp_perc_change < 0, 1, 0))
```

```r
colnames(data)
```

```
##  [1] "Date"
##  [2] "All Groups CPI"
##  [3] "Gross domestic product (Current prices, Millions)"
##  [4] "General government - National Final Consumption Expenditure (Millions)"
##  [5] "General government - National Gross fixed capital formation (Millions)"
##  [6] "cpi_index"
##  [7] "Real_GDP"
##  [8] "Total_Gov_Exp"
##  [9] "diff_rgdp"
## [10] "diff_tge"
## [11] "rgdp_perc_change"
## [12] "recession"
```

4. Setting up the Linear Regression Model

We now fit the linear regression model. Once our model has been fitted, we'll look to perform *Residual Analysis*, which will require us to use `predicted` and `residual` values for each observation in the data.

We regress `diff_rgdp` on `diff_tge`, `recession`, and `diff_tge:recession`.

```r
# Fit the model
lmod <- lm(diff_rgdp ~ (diff_tge + recession)^2, data = data)

# Check the model
summary(lmod)
```

```
##
## Call:
## lm(formula = diff_rgdp ~ (diff_tge + recession)^2, data = data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -12904.2   -860.8   -236.1    521.2   8917.0
##
## Coefficients:
##                      Estimate Std. Error t value             Pr(>|t|)
## (Intercept)         1107.0703   118.2738   9.360 < 0.0000000000000002 ***
## diff_tge               0.7572     0.1580   4.792       0.000002795822 ***
## recession          -2526.6040   381.9224  -6.615       0.000000000215 ***
## diff_tge:recession    -0.5228     0.3769  -1.387                0.167
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1693 on 256 degrees of freedom
##   (1 observation deleted due to missingness)
## Multiple R-squared:  0.2285, Adjusted R-squared:  0.2195
## F-statistic: 25.27 on 3 and 256 DF,  p-value: 0.00000000000002354
```

```r
# Get the fitted (predicted) values
pred_rgdp_change <- fitted(lmod)
data$pred_rgdp_change <- c(NA, pred_rgdp_change)
#head(data)
```

5. Interpreting the model

Here's the interpretation of each coefficient in the regression model:

Model: **`diff_rgdp ~ (diff_tge + recession)^2`**

1. Intercept (1107.07, p-value < 0.001)

- When both `diff_tge` and `recession` are 0:
  - The predicted change in real GDP (`diff_rgdp`) is 1107.07 million AU$.
- This represents the baseline level of `diff_rgdp` in a non-recession year when there is no change in government expenditure (`diff_tge = 0`).

2. `diff_tge` (0.757, p-value < 0.001)

- For each unit increase in `diff_tge` (change in total government expenditure), the predicted `diff_rgdp` increases by 0.757 **million AU$**, **holding `recession` constant**.
- This indicates a positive association between government expenditure changes and GDP growth.

3. `recession` (-2526.60, p-value < 0.001)

- When transitioning from a non-recession year ($recession = 0$) to a recession year ($recession = 1$):
  - The predicted `diff_rgdp` decreases by -2526.60 **million AU$**, **holding `diff_tge` constant**.
- This reflects the significant negative impact of recessions on real GDP growth.

4. Interaction: `diff_tge:recession` (-0.523, p-value $= 0.167$)

- This term represents how the effect of `diff_tge` on `diff_rgdp` changes during a recession ($recession = 1$):
  - For every unit increase in `diff_tge` during a recession year, the effect on `diff_rgdp` decreases by -0.523 **million AU$**, compared to a non-recession year.
- The p-value (0.167) suggests that this interaction effect is **not statistically significant**, so the relationship between `diff_tge` and `diff_rgdp` might not meaningfully change in recession years.

Key Insights

- **`diff_tge`** has a significant positive impact on GDP growth overall.
- **Recession years** significantly lower GDP growth, with a large negative coefficient.
- The interaction term suggests that the effect of government expenditure on GDP during recessions may slightly weaken, but this effect is not statistically significant in the model.

The model's overall performance is reflected in the adjusted R-squared value of **0.2195**, indicating that approximately 22% of the variability in real GDP changes can be explained by the model's predictors. The residual standard error is **1693**, suggesting the average distance that the observed values fall from the regression line. The F-statistic of **25.27** with a highly significant p-value (**$<$ 0.00000000000002354**) implies that at least one predictor variable significantly contributes to explaining the variability in real GDP changes.

Understanding the Multiplier Effect

1. **Baseline Effect (Non-Recession)**:
    - When the economy is **not** in a recession (`recession = 0`), the effect of a unit change in `diff_tge` on the predicted change in real GDP (`diff_rgdp`) is simply given by the coefficient of `diff_tge`, which is **0.757**.
    - This means that for every one-unit increase in `diff_tge`, the change in real GDP increases by **757 million AU$**.
2. **Effect During Recession**:
    - When the economy is in a recession (`recession = 1`), the model includes the interaction term `diff_tge:recession`. To find the overall effect of `diff_tge` on `diff_rgdp` during a recession, you need to combine the `diff_tge` coefficient and the effect of the interaction term:

$$\text{Total Effect during Recession} = \text{Coefficient of diff\_tge} + \text{Coefficient of (diff\_tge} \cdot \text{recession)}$$

    - Plugging in the values:

$$\text{Total effect during recession} = 0.757 + (-0.523) = 0.234$$

    - This means that during a recession, for every one-unit increase in `diff_tge`, the predicted change in real GDP increases by **234 million AU$**.
3. **Difference in the Multiplier**:
    - To see the difference in the multiplier effect of `diff_tge` between the two states:

$$\text{Difference} = \text{Multiplier during non-recession} - \text{Multiplier during recession}$$

    - Thus:

$$\text{Difference} = 0.757 - 0.234 = 0.523$$

    - This means that when the economy is in recession, the effect of `diff_tge` on `diff_rgdp` is reduced by **523 million AU$** per unit change in `diff_tge` compared to when the economy is not in a recession.

Summary

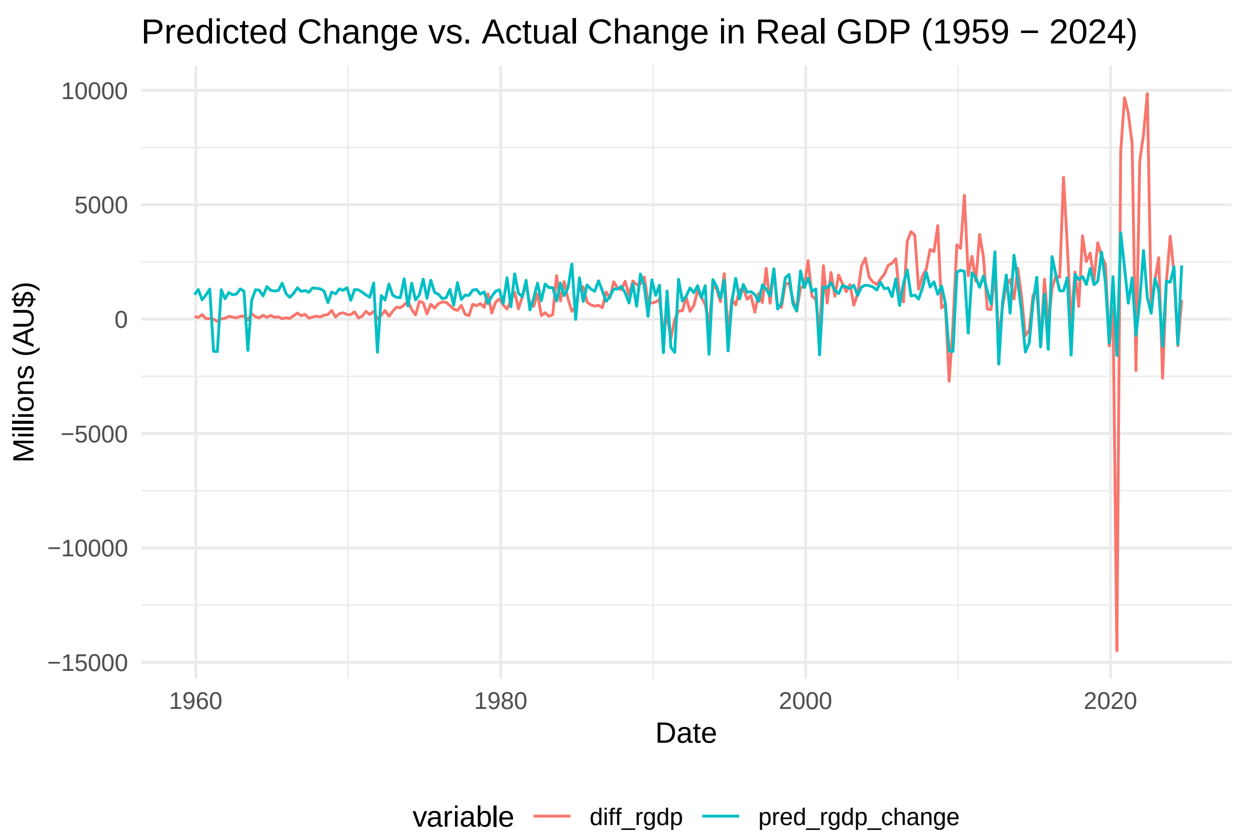
- **In a non-recession**, a unit increase in `diff_tge` leads to an increase of **757 million AU$** in `diff_rgdp`.
- **In a recession**, that same unit increase in `diff_tge` only leads to an increase of **234 million AU$** in `diff_rgdp`.
- The difference of **523 million AU$** highlights how much the impact of `diff_tge` is dampened during a recession compared to periods of economic growth.

6. Plotting Predicted and Actual Real GDP Changes

Let's now plot *Predicted Change in Real GDP* against the *Actual Change in Real GDP*.

```r
# Reshape the data for plotting
data_long <- data %>%
  pivot_longer(cols = c(diff_rgdp, pred_rgdp_change),
               names_to = "variable",
               values_to = "value")

# Plot
data_long %>% ggplot(aes(x = Date, y = value, color = variable)) +
  geom_line() +
  labs(title = "Predicted Change vs. Actual Change in Real GDP (1959 - 2024)",
       x = "Date",
       y = "Millions (AU$)") + theme_minimal() + theme(legend.position = "bottom")
```



From the above graph, we can see that the difference between the actual and predicted Real GDP changes remained stable until early 2020 and the subsequent years after. This correlates well with what happened since 2020, as the large fluctuations in Real GDP change from 2020 onwards can be attributed to the COVID-19 lockdowns, which had a significant impact on economic activity and led to unexpected fluctuations in GDP.

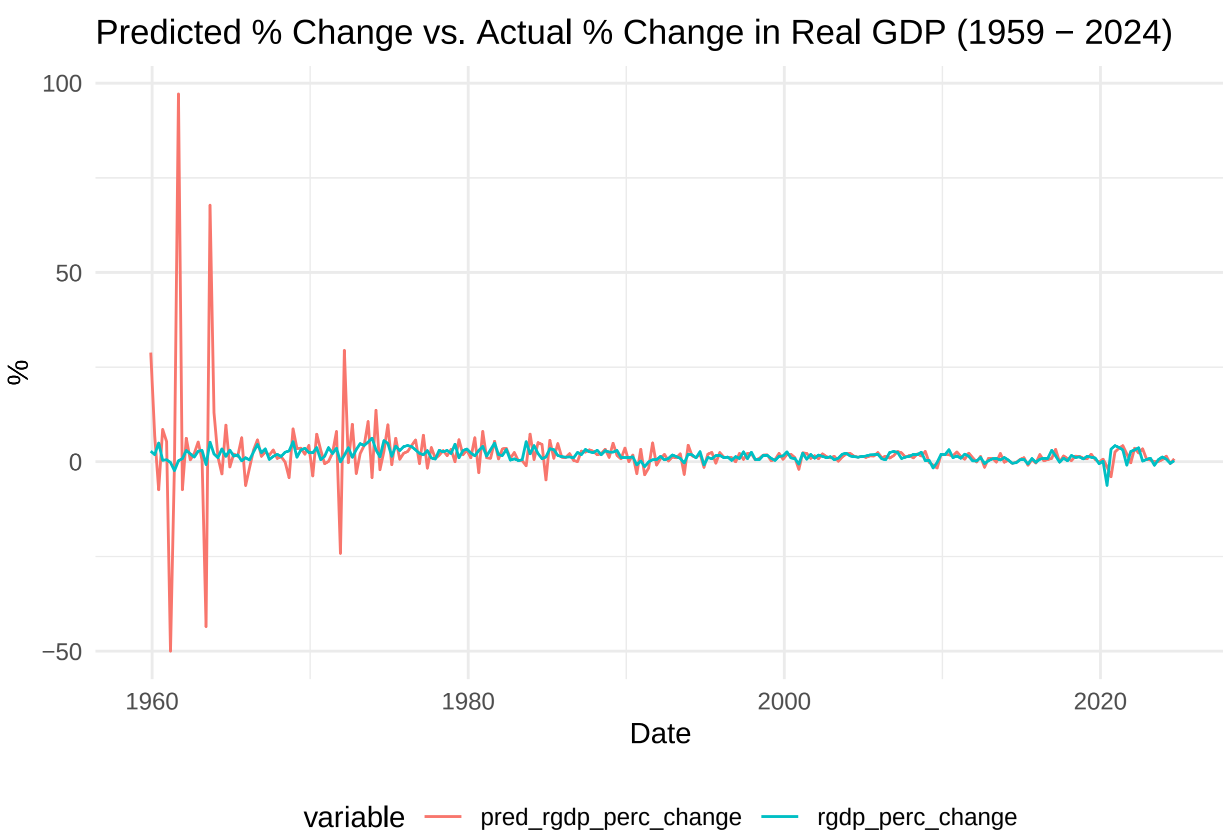
We now take a look at the *Predicted Percentage Change* and *Actual Percentage Change* in Real GDP.

```
# Calculate the predicted GDP
data <- data %>% mutate(
  pred_rgdp = pred_rgdp_change + lag(Real_GDP),
  pred_rgdp = ifelse(is.na(pred_rgdp), 3698.324, pred_rgdp)  # Corrected this line
)

# Calculate the percentage changes in actual Real GDP and predicted Real GDP
data <- data %>% mutate(
  rgdp_perc_change = ((Real_GDP - lag(Real_GDP))/lag(Real_GDP)) * 100,
  pred_rgdp_perc_change = ((pred_rgdp - lag(pred_rgdp))/lag(pred_rgdp)) * 100
)

# Reshape Data
data_long_2 <- data %>%
  pivot_longer(cols = c(rgdp_perc_change, pred_rgdp_perc_change),
               names_to = "variable",
               values_to = "value")

# Plotting Actual Real GDP % Change vs Predicted % Real GDP % Change
ggplot(data_long_2, aes(x = Date, y = value, color = variable)) +
  geom_line() +  # Using default line thickness
  labs(title = "Predicted % Change vs. Actual % Change in Real GDP (1959 - 2024)",
       x = "Date",
       y = "%") + theme_minimal() + theme(legend.position = "bottom")
```



Analyzing percentage changes rather than absolute changes is crucial because it allows for a standardized comparison of economic performance across different time periods and economies. Percentage changes reveal the relative rate of growth or decline, making it easier to understand the significance of fluctuations in relation to the overall size of the economy. This is particularly important during periods of economic disruption, such as the COVID-19 pandemic, where percentage changes more effectively capture the severity of impacts compared to absolute figures.

Comparing the actual percentage change in Real GDP with the predicted percentage change offers a more robust analysis. The significant fluctuations in `pred_rgdp_perc_change` during the early years can be attributed to the limited number of data points. However, as time progresses and the dataset expands, the gap between `rgdp_perc_change` and `pred_rgdp_perc_change` becomes less pronounced. This trend indicates that the distribution of the predicted percentage changes collapses towards the actual percentage changes, which aligns with the *Law of Large Numbers*, suggesting that as the sample size increases, the predictions become more accurate and closely reflect the true values.

7. Model Diagnostics

Model Diagnostics involves *Residual Analysis* and identification of *Influential/Leverage Points.*

1. Residual Analysis

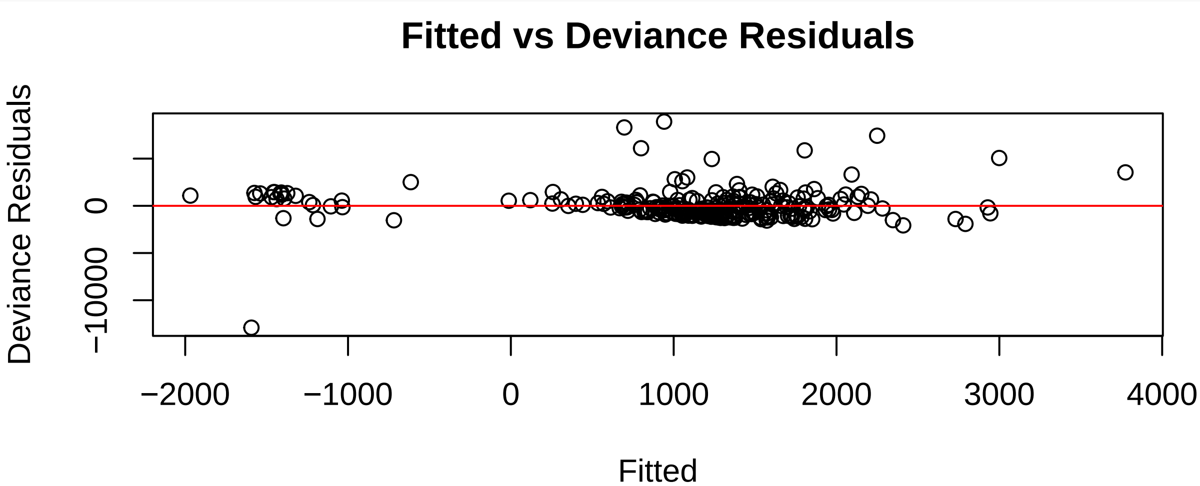
Residual analysis examines the differences between observed and predicted values in a regression model to evaluate its performance and validity. It helps assess whether the model captures data patterns effectively, checks key assumptions like linearity, normality, and constant variance of errors, and identifies potential outliers.

A random scatter in a residuals vs. fitted values plot indicates a good model fit, while patterns suggest violations of assumptions. Additionally, histograms or Q-Q plots can verify the normality of residuals, making residual analysis a critical step in ensuring model reliability and accuracy.

Residual Diagnosis

```
deviance_residuals <- residuals(lmod, "deviance")

plot(fitted(lmod), deviance_residuals,
     main = "Fitted vs Deviance Residuals",
     xlab = "Fitted", ylab = "Deviance Residuals")
abline(h = 0, col = "red")
```



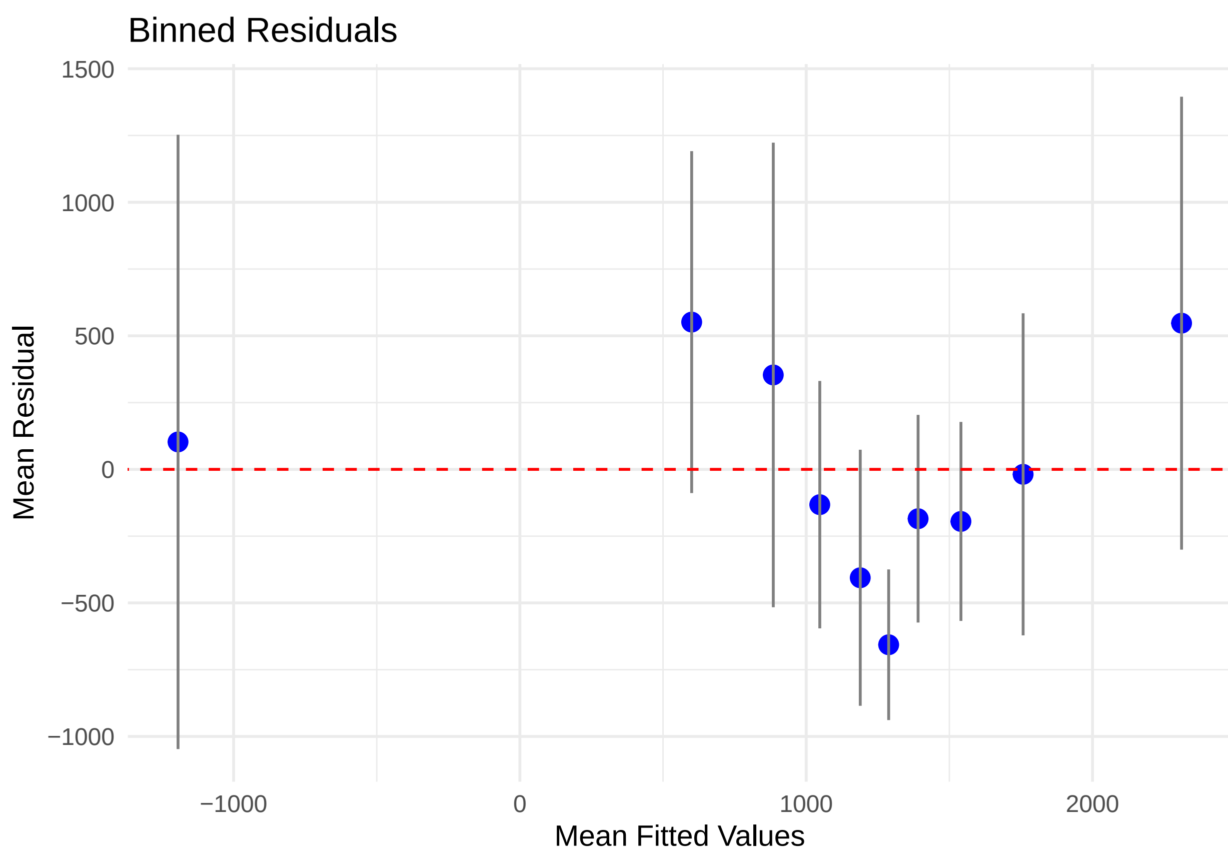
Binned Residuals

```
residual_df <- data %>% mutate(
  residual= c(NA, residuals(lmod)),
  fitted = c(NA, fitted(lmod)),

  bins = cut(fitted, breaks = quantile(fitted, probs = seq(0,1,0.1),
                                       na.rm = TRUE),
               include.lower = TRUE))

binned_resid <- residual_df %>% group_by(bins) %>% summarise(
  mean_fitted = mean(fitted),
  mean_residual = mean(residual),
  se.fit = sd(residual)/sqrt(n()),
  count = n()
)

ggplot(binned_resid, aes(x = mean_fitted, y = mean_residual)) +
  geom_point(size = 3, color = "blue") +
  geom_linerange(aes(ymin = mean_residual - 2 * se.fit,
                     ymax = mean_residual + 2 * se.fit),
                 color = "grey50") +
  geom_abline(intercept = 0, slope = 0, color = "red", linetype = "dashed") +
  labs(title = "Binned Residuals",
       x = "Mean Fitted Values",
       y = "Mean Residual") + theme_minimal()
```



The binned residuals plot shows that 9 out of 10 points have their 95% confidence intervals intersecting the 0-line, indicating that the residuals are generally centered around zero and that the model predictions are unbiased across most fitted value ranges. This suggests the model accurately captures the relationship between the predictors and the response variable for the majority of the data. The single point where the 95% CI does not intersect the 0-line may highlight a minor issue in a specific range of fitted values but does not significantly detract from the overall model performance. Together, these results imply that the model provides a good fit, with no major violations of assumptions or systematic biases detected.

2. Leverage and Influential Points

Hat values and Cook's distance are diagnostic tools used to identify influential data points in regression analysis. **Hat values** measure leverage, indicating how far an observation's predictor values are from the mean predictor values. High hat values suggest the data point has a large influence on the fitted values due to its position in the predictor space. Typically, observations with hat values much larger than $\frac{2p}{n}$, where p is the number of predictors and n is the sample size, are considered leverage points. **Cook's distance**, on the other hand, assesses how much an observation influences the overall regression model, combining both leverage and the size of the residual. Large Cook's distance values indicate influential points that disproportionately affect the regression coefficients. Both metrics are essential for detecting and addressing potential anomalies to ensure model robustness.

Cook's Distance

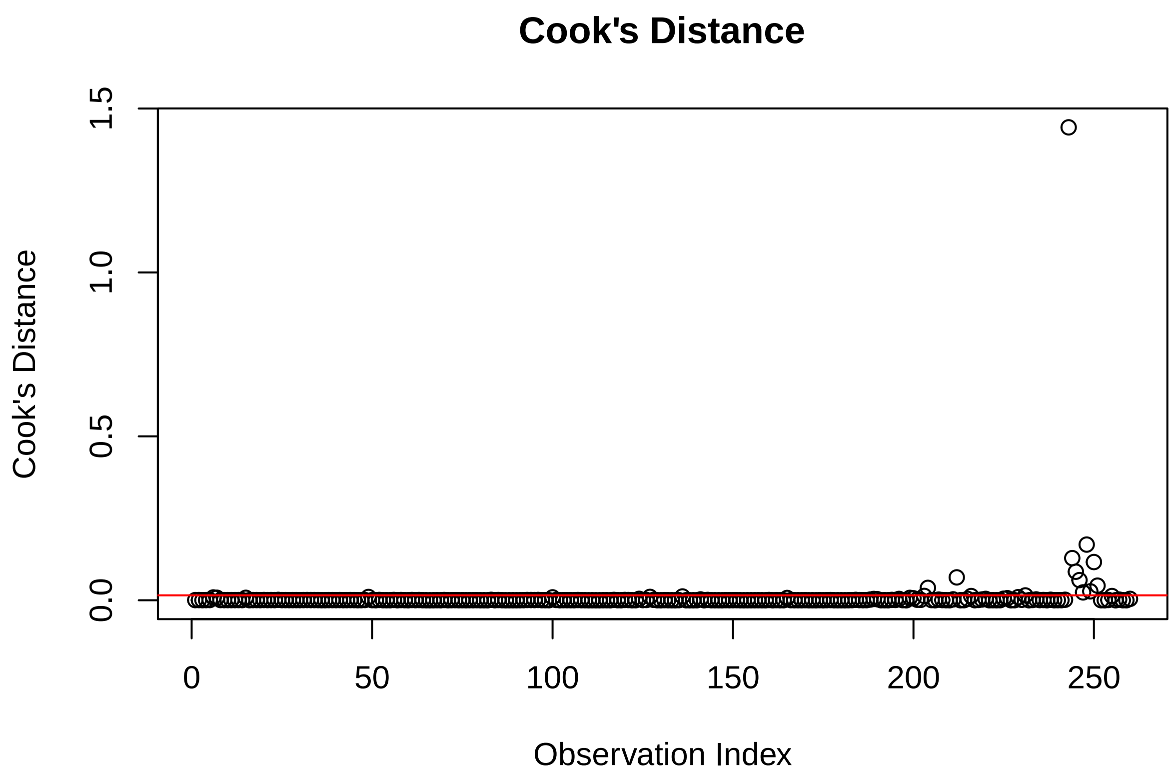
```r
# Cooks threshold for Influential points: 4/261 = 0.015
cooks_dist <- cooks.distance(lmod)
plot(cooks_dist, main = "Cook's Distance", xlab = "Observation Index",
     ylab = "Cook's Distance")
abline(h = 0.015, col = "red")

# looks like there are a couple of observations that have high influence on the
# model.

data$cooks_dist <- c(NA, cooks_dist)

data %>% filter(cooks_dist > 0.015) %>%
  dplyr::select(Date, Real_GDP, Total_Gov_Exp, diff_rgdp, diff_tge,
                cooks_dist)
```

```
## # A tibble: 11 x 6
##    Date                Real_GDP Total_Gov_Exp diff_rgdp diff_tge cooks_dist
##    <dttm>                 <dbl>         <dbl>     <dbl>    <dbl>      <dbl>
##  1 2010-09-01 00:00:00  175551.         35510     1895.    -2274     0.0378
##  2 2012-09-01 00:00:00  188474.         38730     -884.    -2342     0.0698
##  3 2020-06-01 00:00:00  218593.         58332   -14498.     -742     1.44
##  4 2020-09-01 00:00:00  225909.         61855     7316.     3523     0.129
##  5 2020-12-01 00:00:00  235585.         63364     9676.     1509     0.0870
##  6 2021-03-01 00:00:00  244583.         62822     8999.     -542     0.0615
##  7 2021-06-01 00:00:00  252261.         63743     7677.      921     0.0240
##  8 2021-09-01 00:00:00  250013.         66735    -2248.     2992     0.170
##  9 2021-12-01 00:00:00  256915.         66329     6903.     -406     0.0273
## 10 2022-03-01 00:00:00  264981.         68828     8066.     2499     0.117
## 11 2022-06-01 00:00:00  274839.         68609     9858.     -219     0.0445
```



The Cook's Distance analysis highlights significant influential points in the data, particularly from 2020-06-01 to 2022-03-01, a period marked by economic disruptions due to the pandemic. Observations like 2020-06-01 (-14497.67) and 2020-12-01 (9675.83) exhibit large deviations, suggesting they strongly impact the regression model. These values exceed the typical threshold for Cook's Distance (0.015), indicating their high leverage and influence on model coefficients. This pattern underscores the importance of assessing whether these points are genuine reflections of economic shifts or outliers requiring further analysis to ensure model robustness.

Leverage Points

```
# Leverage threshold: 8/261 = 0.031
data$leverage <- c(NA, hatvalues(lmod))

data %>% filter(leverage > 0.030) %>%
  dplyr::select(Date, Real_GDP, Total_Gov_Exp, diff_rgdp, diff_tge, leverage) %>%
  tail(10)
```

```
## # A tibble: 10 x 6
##    Date                Real_GDP Total_Gov_Exp diff_rgdp diff_tge leverage
##    <dttm>                 <dbl>         <dbl>     <dbl>    <dbl>    <dbl>
##  1 2016-03-01 00:00:00  199091.         45501     1336.     2145   0.0347
##  2 2017-06-01 00:00:00  212011.         47203     -212.     -663   0.0773
##  3 2019-06-01 00:00:00  231439.         55780     2758.     2406   0.0437
##  4 2019-12-01 00:00:00  232657.         58092    -1177.     1644   0.123
##  5 2020-06-01 00:00:00  218593.         58332   -14498.     -742   0.0835
##  6 2020-09-01 00:00:00  225909.         61855     7316.     3523   0.0960
##  7 2021-09-01 00:00:00  250013.         66735    -2248.     2992   0.351
##  8 2022-03-01 00:00:00  264981.         68828     8066.     2499   0.0473
##  9 2023-06-01 00:00:00  277165.         69550    -2584.      989   0.0659
## 10 2024-06-01 00:00:00  283285.         73835    -1161.     1341   0.0923
```

Influential points in a regression analysis are data observations that significantly affect the model's fitted values and parameter estimates. These points can arise from high leverage, meaning they have extreme predictor values, or from having large residuals, indicating they do not conform to the model's predictions. Detecting influential points is critical because they can distort the regression results, leading to misleading conclusions. Common diagnostic tools, such as Cook's Distance and hat values, help identify these points, allowing researchers to assess their impact and decide whether to investigate them further, potentially excluding them from the analysis if they are determined to be outliers or anomalies that do not represent the underlying population.

8. Conclusion

This analysis provides valuable insights into the fiscal multiplier's effects during different economic conditions, particularly emphasizing the substantial negative impact of recessionary periods on the Australian economy.

The linear regression model fitted to analyze the effect of the fiscal multiplier on the change in real GDP (`diff_rgdp`) includes government spending changes (`diff_tge`) and a recession indicator, along with their interaction. The model reveals that the intercept is significant, with an estimate of `1107.07`, indicating that when both predictors are zero, the predicted change in real GDP is around `1107 million AU$`. The coefficient for `diff_tge` is `0.7572`, suggesting that for every one-unit increase in government spending, the real GDP change increases by approximately `757 million AU$`. Conversely, the recession variable shows a negative impact, with a coefficient of `-2526.6040`, indicating a substantial decline in real GDP during recessionary periods. However, the interaction term (`diff_tge:recession`) is not statistically significant, with a p-value of **`0.167`**, suggesting that the relationship between government spending changes and real GDP does not differ significantly during recessions compared to non-recession periods.

The linear regression model exploring the effects of fiscal policy on the change in real GDP (`diff_rgdp`) offers critical insights into the dynamics of government spending and economic performance, particularly during recessionary and non-recessionary periods. The significant positive coefficient for `diff_tge` (0.7572) indicates that increases in government spending are associated with substantial increases in real GDP. This result aligns with the Keynesian economic theory, which posits that fiscal policy, particularly through government expenditure, can stimulate economic activity during periods of economic slack. In essence, when the government injects money into the economy—whether through infrastructure projects, social programs, or direct transfers—it can boost aggregate demand, leading to a multiplier effect where each dollar spent generates additional economic activity.

Conversely, the significant negative coefficient for the `recession` variable (-2526.6040) highlights the detrimental impact of economic downturns on real GDP. This finding underscores the necessity for counter-cyclical fiscal policies during recessions. The ability of fiscal policy to mitigate economic downturns is particularly relevant in light of the observed lack of significance for the interaction term (`diff_tge:recession`). This suggests that while government spending remains essential during recessions, its effectiveness does not vary significantly compared to non-recessionary periods. The Keynesian framework supports this, indicating that even in downturns, increased government spending is crucial to restore confidence and stimulate economic growth. The model's adjusted R-squared value of 0.2195 suggests that while fiscal policy plays a substantial role in influencing real GDP, other factors also contribute to this economic variability. Overall, the analysis reinforces the theoretical underpinnings of fiscal policy as a vital tool for managing economic fluctuations and promoting stability.

9. References

1. Munoz-Garcia, F. (Year). *Advanced Microeconomic Theory: An Intuitive Approach with Examples.*
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