The Macroeconomic Effects of Fiscal Adjusments in The UK

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1 Abstract

2 Introduction

3 Literature Review

3.1 Costs of high indebtedness

Sutherland, Hoeller, and Merola [3] draw attention to the fiscal challenges facing countries following the Global Financial Crisis, noting that gross government debt has exceeded 100% of GDP for the OECD as an aggregate. This has been exacerbated following the Covid pandemic where governments implemented fiscal measures to mitigate the economic costs of the pandemic. Makin and Layton (2021) highlight that governments must employ fiscal responsibility to protect their economies from the risks that high indebtedness exposes them to. Warmedinger, Checherita-Westphal, and De Cos [4] emphasise the importance of public debt sustainability for ensuring macroeconomic stability. There are several mechanisms through which excessive debt could harm the economy. For instance, concerns regarding public finances could reduce business confidence, leading to decreased investment and thus a slowdown in growth. Additionally, strained public finances could hinder the ability of economies to react counter cyclically to economic shocks. This rationale is supported by the IMF (2023) who argue that economies should rebuild their fiscal buffers to reduce their debt vulnerabilities. Therefore, fiscal consolidation is clearly needed to ensure the long-term resilience of the economy. As a target, Sutherland, Hoeller, and Merola [3] propose that countries should aim to bring debt levels towards 50% of GDP: a figure which would require the UK to halve its current debt levels (ONS, 2025). The IMF (2023) argues that to stabilise GDP, fiscal adjustments should be in the region of up to 4% of GDP. Thus, achieving this objective would require significant fiscal adjustments, motivating further research to support the transition towards more sustainable public finances. Alesina, Favero, and Giavazzi (2012) find that permanent fiscal adjustments have lower output costs, interpreting this result as due to business confidence. (easier to forecast when fiscal adjustments are more predictable? Thus have less of a effect on confidence)

Kumar and Woo (2015) find that greater indebtedness is associated with lower economic growth. They also find noticeable nonlinearities in this result, with the most severe effect when public indebtedness exceeds 90% of GDP. Given the aforementioned level of public indebtedness in the UK …
Blanchard (2019) argue that even when the interest rate is less than the growth rate, and thus there is no fiscal cost of high indebtedness, there may still be a welfare cost due to reduced capital accumulation.

3.2 Fiscal Consolidaton

While the importance of fiscal consolidation has been highlighted, it is crucial that these measures are not at the expense of the broader economy. By investigating forecast errors for a sample of European countries, Blanchard and Leigh [1] find that larger anticipated fiscal consolidation was associated with lower growth. This result was interpreted as due to the fiscal multiplier being greater than anticipated by forecasters. Consequently, fiscal tightening would have further dampened demand, and thus improvements in fiscal consolidation would be offset by reduced growth. Gechert (2019) adopt a similar methodology, finding that austerity measures in the Euro Area deepened the crisis, contributing to hysterisis effects. Fatas and Summers (2018) extend this research, investigating the long-term effects that fiscal adjustments have had on GDP. Their analysis suggests that fiscal consolidations have failed to lower the debt-to-GDP ratio due to a hysteresis effect of contractionary fiscal policy. This research underscores the need for effectively quantifying fiscal multipliers to understand potential trade-offs between various economic objectives. Ilzetzki, Mendoza, and Végh [2] provide further insight into the fiscal multiplier, suggesting that the heterogeneity in the estimates reported in the literature can be attributed to differences in structural characteristics of the economy considered. This reinforces the importance of research to better understand the fiscal multiplier for different policy instruments, particularly as this may vary across countries and over time. Additionally, Alesina et al (2015) compare multipliers due to spending and tax adjustments. They find that … have more severe effects, attributing this to reduced business confidence. Alesina et al (2002) investigate the effect of fiscal policy on investment.

3.3 Synthesis of Methodology

Capek and Cuasera (2020) simulate 20 million fiscal multipliers, highlighting how methodological choices contribute to the heterogeneity in estimates of fiscal multipliers prevalent in the literature. Consequently, they advocate for explicitly outlining modelling choices and assumptions. Similarly, Gechert (2017) provides a synthesis of the methodologies used to estimate fiscal multipliers, highlighting competing definitions for the fiscal multiplier and possible issues in its estimation. Among these issues, Gechert (2017) highlight potential omitted variable bias in the VAR model (motivating the use of additional controls such as the price level and real interest rate), anticipation effects (cf Leepper + Zha fiscal foresight), and nonlinearities.

Structural Vector Autoregressions (SVARs) have been prominent in the literature to estimate fiscal multipliers. Various approaches to identification have been used, with XXX (YYYY) noting that after accounting for the empirical specification, the competing identifying approaches have little effect on the estimated multipliers. Blanchard and Perotti (2002) pioneered this strand of

the research, leveraging methodologies previously popularised by the monetary economics. To identify their SVAR, Blanchard and Perotti leverage instituional information. They provide a definition for the fiscal variables and highlight that government expenditure is predetermined within a quarter. Recursive measures to identfication have been employed by Fatas and Mihov (YYYY) and Fernandex (2008). Fernandez argues that Uhlig and Mountford (200Y) apply restrictions on the signs of the impulse response functions. Caldara and Kamps (2008) reviews the literature on SVAR identification. Caldara and Kamps (2017) introduce a new approach for identification.

4 Data

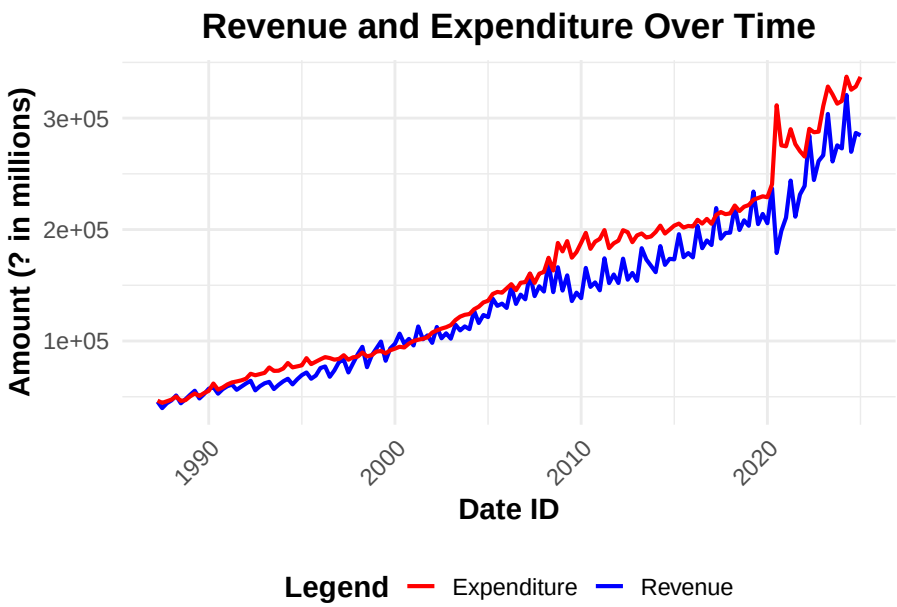
Fiscal variables are at the general level

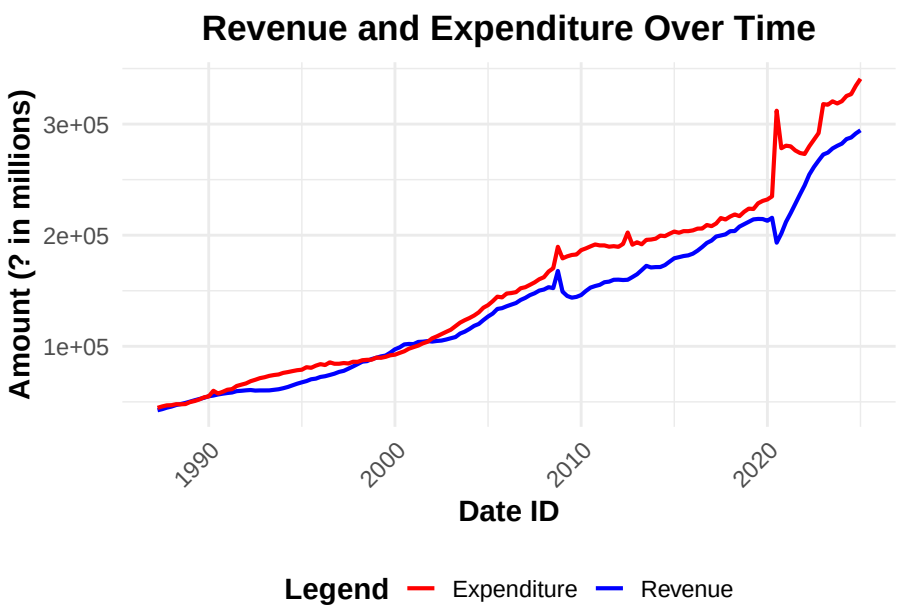
We use quarterly data for the UK economy covering the period 1987 – 2023. The empirical model is a 5-dimensional VAR model consisting of government expenditure (g_t), net government taxes (nt_t), GDP (G_t), the GDP deflator inflation rate (π_t), and the mean of the 3 month treasury rate (τ_t). Following Fernandez (2006), the natural logarithm of these variables is used, with the exception of the treasury rate which enters the model in levels. Furthermore, the fiscal variables and GDP are used in real terms.

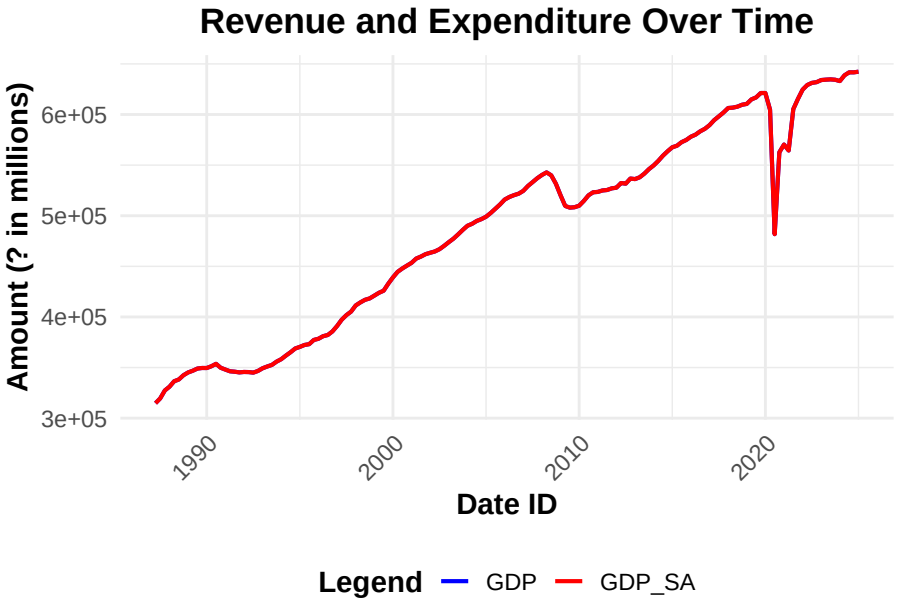
The fiscal variables used follow the European System of Accounts (ESA, 2010). This closely follows the literature. In particular, government expenditure represents the outflows associated with government activities, including consumption, investment, and transfers. The inflows to the government, government revenue, consists of receipts net of transfer and interest payments. Cf Blanchard and Perotti (2002)

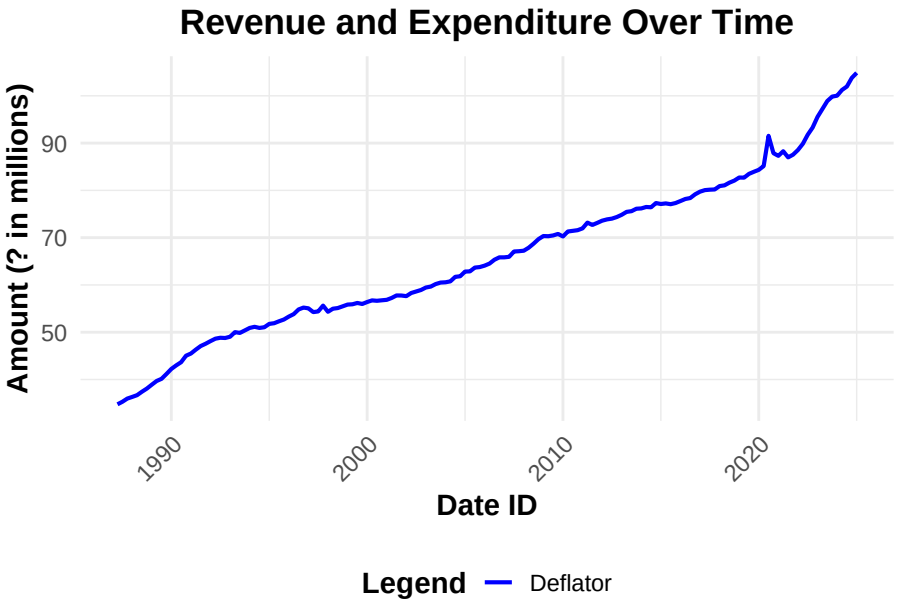
NB need to confirm regarding local, central, and general government

5 Plots


Revenue and Expenditure Over Time
Amount (? in millions)
3e+05
2e+05
1e+05
1990
2000
2010
2020
Date ID
Legend
Expenditure
Revenue


Revenue and Expenditure Over Time
Amount (? in millions)
3e+05
2e+05
1e+05
1990
2000
2010
2020
Date ID
Legend
Expenditure
Revenue


Revenue and Expenditure Over Time
Amount (? in millions)
6e+05
5e+05
4e+05
3e+05
1990
2000
2010
2020
Date ID
Legend
GDP
GDP_SA


Revenue and Expenditure Over Time
Amount (? in millions)
90
70
50
1990
2000
2010
2020
Date ID
Legend
Deflator

6 Econometric Methodology

This section outlines the VAR methodology that will be employed by this research. We define the 5-dimensional vector of endogenous variables as:

$$X_t = \begin{pmatrix} G_t \\ R_t \\ GDP_t \\ \tau_t \\ P_t \end{pmatrix}$$

The reduced-form VAR model can be written as:

$$X_t = A_1 X_{t-1} + A_2 X_{t-2} + \cdots + X_p Y_{t-p} + \epsilon_t$$

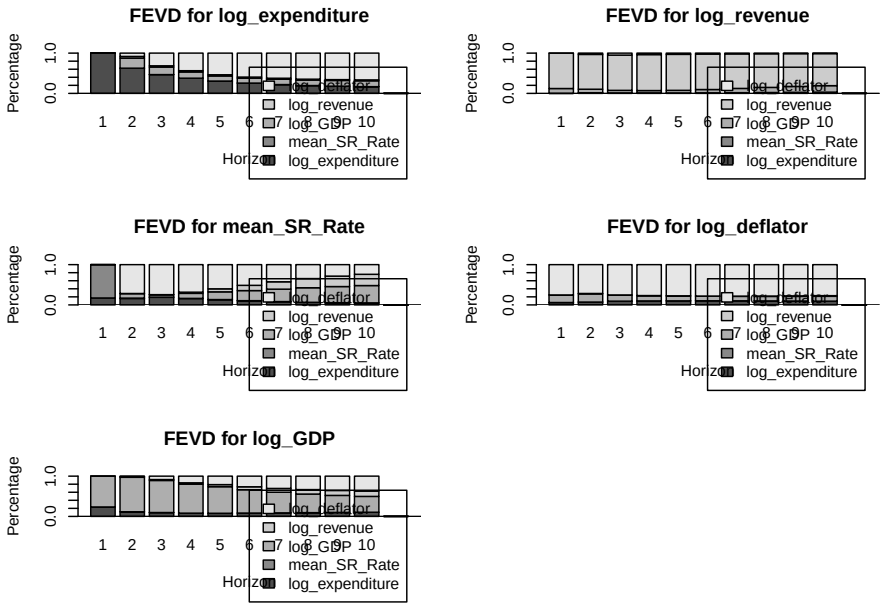
where ϵ_t is the vector of reduced-form residuals and p determines the lag length. In line with XXX we assume the model contains 4 lags. Given the use of quarterly data, this can be interpreted as lags of the model variables having a direct affect for up to a year. This use of lag is supported by the Akaike Information Criteria.

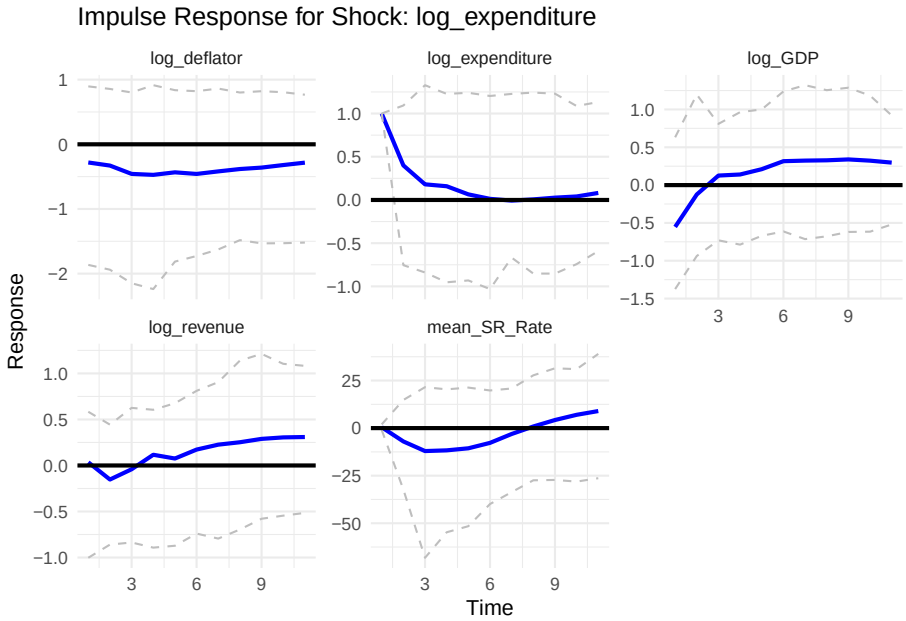
Discuss Empirical model, lag structure, data sources, potentially features of the data

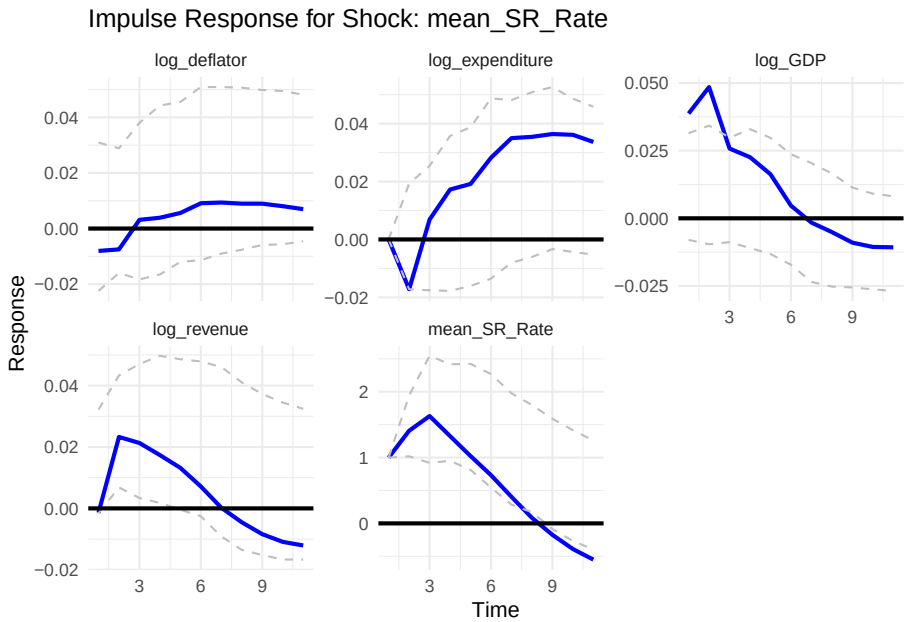
```
## AIC(n)  HQ(n)  SC(n) FPE(n)
##      2      2      1      2
```

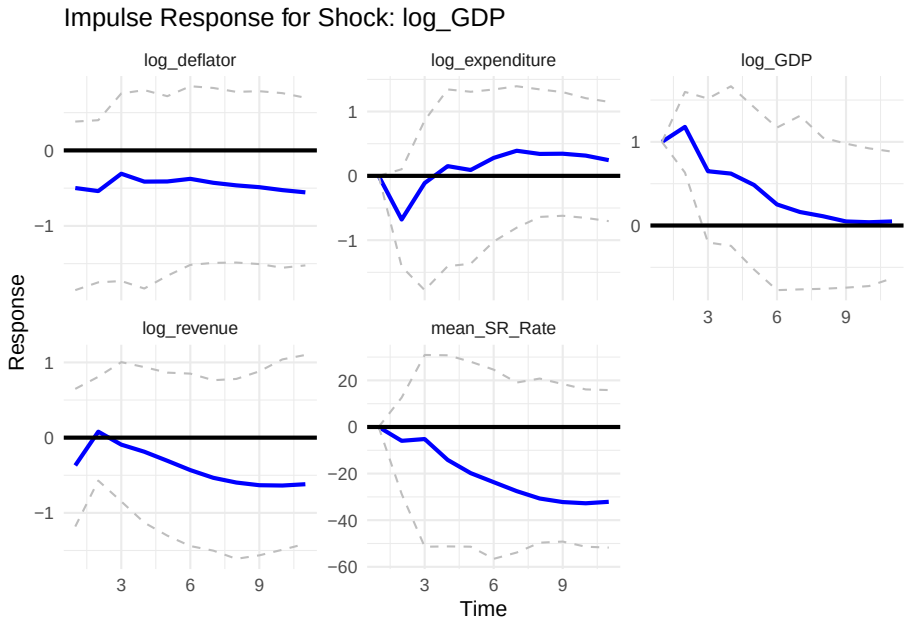
Note: VAR analysis requires stability of the system. Need to find code to ensure the eigenvalues of the autoregressive roots lie within the unit circle.

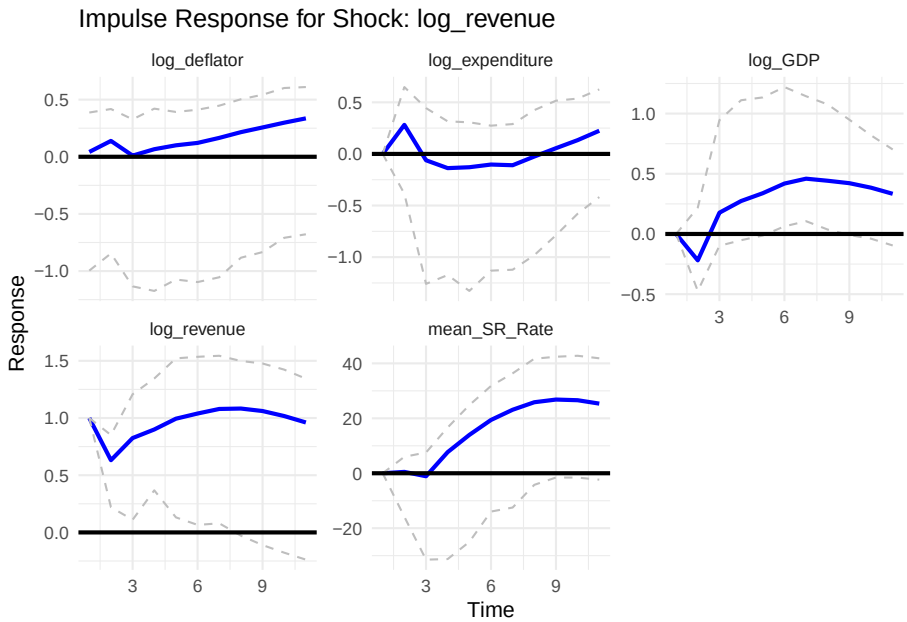
```
##
## SVAR Estimation Results:
## ========================
##
##
## Estimated A matrix:
##                 log_expenditure mean_SR_Rate log_GDP log_revenue log_deflator
## log_expenditure          1.0000      0.00000  0.0000     0.00000            0
## mean_SR_Rate            -0.4557      1.00000  0.0000     0.00000            0
## log_GDP                  0.5704     -0.03874  1.0000     0.00000            0
## log_revenue              0.1758     -0.01291  0.3696     1.00000            0
## log_deflator             0.5544     -0.01072  0.4828    -0.04213            1
```

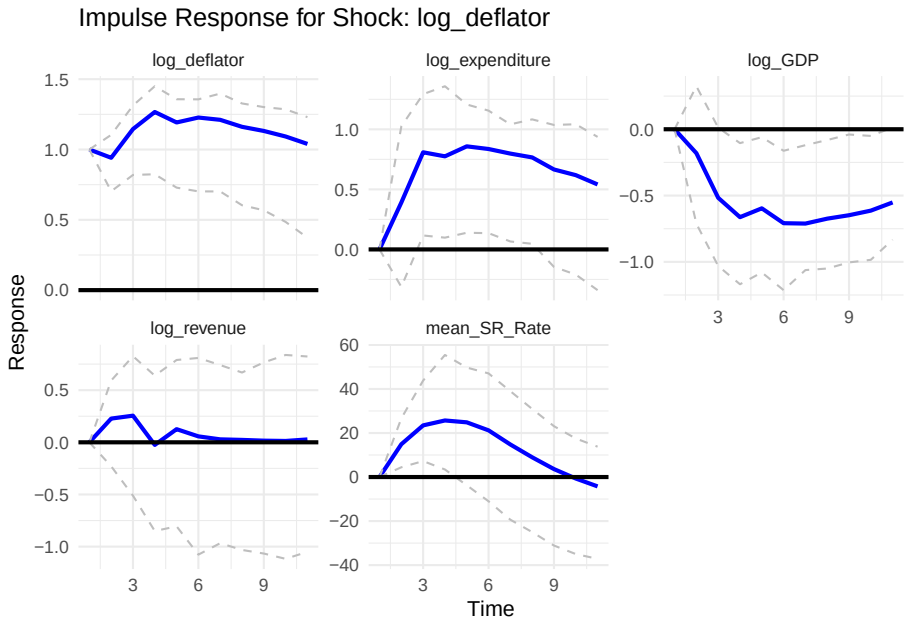

FEVD for log_expenditure
FEVD for log_revenue
FEVD for mean_SR_Rate
FEVD for log_deflator
FEVD for log_GDP
Percentage
0.0
1.0
1 2 3 4 5 6 7 8 9 10
Horizon
log_deflator
log_revenue
log_GDP
mean_SR_Rate
log_expenditure


Impulse Response for Shock: log_expenditure
log_deflator
log_expenditure
log_GDP
log_revenue
mean_SR_Rate
Response
Time


Impulse Response for Shock: mean_SR_Rate
log_deflator
log_expenditure
log_GDP
log_revenue
mean_SR_Rate
Response
Time


Impulse Response for Shock: log_GDP
log_deflator
log_expenditure
log_GDP
log_revenue
mean_SR_Rate
Response
Time


Impulse Response for Shock: log_revenue
log_deflator
log_expenditure
log_GDP
log_revenue
mean_SR_Rate
Response
Time


Impulse Response for Shock: log_deflator
log_deflator
log_expenditure
log_GDP
log_revenue
mean_SR_Rate
Response
Time

7 Identification

How we recover the structural shocks to conduct meaningful analysis. Recall The reduced form residuals are correlated and lack an economic interpretation. Identification measure requires economic justification. Use short run restrictions with a recursive structure for this. Following Fernandez (2006)

Recovering Structural Shocks

Let X_t be the vector of variables:

$$X_t = \begin{pmatrix} G_t \\ R_t \\ GDP_t \\ T_t \\ P_t \end{pmatrix}$$

The reduced-form VAR model can be written as:

$$X_t = A_1 X_{t-1} + A_2 X_{t-2} + \cdots + A_p X_{t-p} + \epsilon_t$$

where ϵ_t is the vector of reduced-form residuals. To recover the structural shocks u_t, we assume:

$$\epsilon_t = B u_t$$

$B^{-}1$ is the structural impact multiplier matrix.

where B is a lower triangular matrix. The structural shocks u_t are assumed to be uncorrelated and have unit variance.

The matrix B can be obtained using Cholesky decomposition of the covariance matrix of the reduced-form residuals Σ_ϵ:

$$\Sigma_\epsilon = E[\epsilon_t \epsilon_t'] = BB'$$

Given the recursive ordering (G, R, GDP, T, P), the matrix B has the form:

$$B = \begin{pmatrix} b_{11} & 0 & 0 & 0 & 0 \\ b_{21} & b_{22} & 0 & 0 & 0 \\ b_{31} & b_{32} & b_{33} & 0 & 0 \\ b_{41} & b_{42} & b_{43} & b_{44} & 0 \\ b_{51} & b_{52} & b_{53} & b_{54} & b_{55} \end{pmatrix}$$

Thus, the structural shocks u_t can be recovered as:

$$u_t = B^{-1}\epsilon_t$$

Killian and Lutkepohl (2017) highlight that … is not sufficient for identification of the structural VAR parameters: the identifying assumptions must also be motivated by economic rationale. Following Fernandez (2006), I outline the assumptions captured by the matrix B.

1) (implementation lags) Quarterly data so G predetermined wrt rest of variables within the quarter.

a. See Blanchard and Perotti (2002),

2) Given physical constraints, the interest rate is assumed not to react contemporaneously to price, net taxes, or output.

3) However monetary policy shocks are assumed to affect output, net taxes, and prices contemporaneously. Fernandez (2006) justifies this assumptions by noting that interest movements are anticipated and thus they can be transmitted to real variables relatively quickly. NB on the appropriateness of the assumption that interest rate does not react to price/ output.
4) Due to price stickiness, prices do not react contemperaneously to shocks to GDP,
5) Due to physical constraints in adjusting consumption and investment, net taxes are assumed not to affect economic activity.

Applying these zero restrictions to the … we obtain the lower triangular matrix, B, which can be recovered from the variance-covariance matrix of the reduced form residuals.

8 Results

Ramey (2019) define fiscal multipliers: "change in output due to a change in spending or taxes", and highlight the risk of ignoring fiscal foresight. Gechert (2017)

9 Robustness

10 Discussion/ Policy Implications

11 Conclusion

12 Bibliography

References

[1] O.J. Blanchard and D. Leigh. "Growth forecast errors and fiscal multipliers". In: *American Economic Review* 103.3 (2013), pp. 117–120.

[2] E. Ilzetzki, E.G. Mendoza, and C.A. Végh. "How big (small?) are fiscal multipliers?" In: *Journal of Monetary Economics* 60.2 (2013), pp. 239–254.

[3] D. Sutherland, P. Hoeller, and R. Merola. "Fiscal consolidation: How much, how fast and by what means?" In: (2012).

[4] T. Warmedinger, C.D. Checherita-Westphal, and P.H. De Cos. "Fiscal multipliers and beyond". In: *ECB Occasional Paper* 162 (2015).

13 Technical Appendix

```r
# library(knitr)
# library(stargazer)
# library(clipr)
#library(kableExtra)

library(ggplot2)
library(knitr)
library(ivreg)
library(ggdag)
library(data.table)
library(dplyr)
library(tidyr)
library(stargazer)
library(clipr)
library(tibble)
library(lubridate)
# install.packages("seasonal")
library(seasonal)
```

```r
lapply(c("ggplot2", "dplyr", "data.table", "lubridate", "janitor", "broom", "tibble", "tidyr
       require, character.only = TRUE)

# knitr::opts_chunk$set(echo = FALSE)
knitr::opts_chunk$set(echo = FALSE, warning = FALSE, message = FALSE)




df <- fread("D:/Samid work/University/KCL - Econ and Policy/Dissertation/Data/GDP.csv", skip


# Filter the data frame to exclude rows where the column 'title' matches any of the specific


filtered_df <- df %>%
  # Keep only the quarterly data
  filter(nchar(CDID) == 7 & substr(CDID, 6, 6) == "Q") %>%
  # Select relevant columns and rename them
  dplyr::select(CDID, Deflator = L8GG, GDP = ABMI) %>%
  # Create new columns and convert types
  mutate(
    Year = as.numeric(substr(CDID, 1, 4)),
    Quarter = substr(CDID, 6, 7),
    Q = as.numeric(substr(CDID, 7, 7)),
    Deflator = as.numeric(Deflator),
    GDP = as.numeric(GDP)
  ) %>%
  # Filter by year (can modify for testing)
  filter(Year >= 1987)



fiscal_raw <- fread("D:/Samid work/University/KCL - Econ and Policy/Dissertation/Data/Fiscal

fiscal_proc <- fiscal_raw %>%
  dplyr::select(Date_ID = Transaction, Revenue = OTR, Expenditure = OTE) %>%
  subset(Date_ID !=  "Dataset identifier code" & Date_ID != "Identifier") %>%
  mutate(Year = as.numeric(gsub("\\D", "", Date_ID)),
         Period = gsub("\\d{4}", "", Date_ID))  %>%
  mutate(
    Q = case_when(
      Period == "Jan to Mar " ~ 1,
```

```
      Period == "Apr to Jun " ~ 2,
      Period == "Jul to Sep " ~ 3,
      Period == "Oct to Dec " ~ 4
      ),
    Unique_Period = Year +(Q/4)

  ) %>%
  # Convert to numeric and multiply by 1 million so values as these will later be made into
  mutate(Revenue = as.numeric(gsub(",", "", Revenue) ),
         Expenditure = as.numeric(gsub(",", "", Expenditure )))

# join GDP deflator and GDP data

population <- fread("D:/Samid work/University/KCL - Econ and Policy/Dissertation/Data/Popula
                    skip = 4,
                    header = TRUE) %>%
  subset(`Country Name` == "United Kingdom") %>%
  t() %>%
  as.data.frame() %>%
  rownames_to_column(var = "Year") %>%
  rename(Population = V1 ) %>%
  filter(grepl("^\\d{4}$", Year)) %>%
  mutate(Year = as.numeric(Year),
         Population = as.numeric(Population))

Interest_SR <- fread("D:/Samid work/University/KCL - Econ and Policy/Dissertation/Data/3 Mon
  mutate(Date = dmy(Date),
         month = month(Date),
         Year = year(Date),
         Q = case_when(
           month %in% 1:3 ~ 1,
           month %in% 4:6 ~ 2,
           month %in% 7:9 ~ 3,
           month %in% 10:12 ~ 4
         )) %>%
  group_by(Year, Q) %>%
  summarize(mean_SR_Rate = mean(SR_Rate, na.rm = TRUE))

SONIA <- fread("D:/Samid work/University/KCL - Econ and Policy/Dissertation/Data/Bank of Eng
  mutate(Date = dmy(Date),
         month = month(Date),
         Year = year(Date),
         Q = case_when(
           month %in% 1:3 ~ 1,
           month %in% 4:6 ~ 2,
```

```
            month %in% 7:9 ~ 3,
            month %in% 10:12 ~ 4
          )) %>%
  group_by(Year, Q) %>%
  summarize(mean_SONIA = mean(SONIA, na.rm = TRUE))




# Policy_Rate <- fread("D:/Samid work/University/KCL - Econ and Policy/Dissertation/Data/Pol
#   mutate(Date = dmy(`Date Changed`)) %>%
#   mutate(month = month(Date),
#          Year = year(Date),
#          Q = case_when(
#            month %in% 1:3 ~ 1,
#            month %in% 4:6 ~ 2,
#            month %in% 7:9 ~ 3,
#            month %in% 10:12 ~ 4
#          )) %>%
#   group_by(Year, Q) %>%
#   summarize(mean_SONIA = mean(Rate, na.rm = TRUE))

# str(Policy_Rate)



Policy_Rate <- fread("D:/Samid work/University/KCL - Econ and Policy/Dissertation/Data/Polic
  mutate(Date = parse_date_time(`Date Changed`, orders = "dmy"),
         Q = quarter(Date),
         Year = year(Date)) %>%
  group_by(Year, Q) %>%
  summarise(mean_SR_Rate = mean(Rate, na.rm = TRUE), .groups = "drop") %>%
  complete(Year = full_seq(Year, 1), Q = 1:4) %>%  # Ensure all Year-Quarter combinations
  arrange(Year, Q) %>%
  fill(mean_SR_Rate, .direction = "down")  # Fill missing rates by propagating the previous



data <- fiscal_proc %>%
  left_join(filtered_df, by = c("Q" = "Q", "Year" = "Year")) %>%
  left_join(Policy_Rate, by = c("Q" = "Q", "Year" = "Year")) %>%
  left_join(population, by = c("Year" = "Year")) %>%
# Convert variables to per capita, note revenue, expenditure, and GDP are in £ million so ne
  mutate(RevenuePerCapita = (Revenue *10^6) /Population,
```

```r
         ExpenditurePerCapita = (Expenditure *10^6) /Population,
         GDPPerCapita = (GDP *10^6) /Population) %>%

  # Seasonal Adjustment of data using X-13ARIMA-SEATS
   mutate(Revenue_SA = final(seas(ts(Revenue, start = min(Year), frequency = 4))),
         Expenditure_SA = final(seas(ts(Expenditure, start = min(Year), frequency = 4))),
         GDP_SA = final(seas(ts(GDP, start = min(Year), frequency = 4)))) %>%

# Convert variables (except interest rate) to logs
  mutate(log_revenue = log(Revenue_SA *10^6),
         log_expenditure = log(Expenditure_SA *10^6),
         log_GDP = log(GDP_SA *10^6),
         log_deflator = log(Deflator))


model_data <- data %>%
  dplyr::select(CDID, log_expenditure, mean_SR_Rate, log_GDP, log_revenue,  log_deflator)





ggplot(data, aes(x = Unique_Period)) +
  geom_line(aes(y = Revenue, color = "Revenue"), size = 1) +
  geom_line(aes(y = Expenditure, color = "Expenditure"), size = 1) +
  labs(
    x = "Date ID",
    y = "Amount (? in millions)",
    title = "Revenue and Expenditure Over Time",
    color = "Legend"
  ) +
  scale_color_manual(values = c("Revenue" = "blue", "Expenditure" = "red")) +
  theme_minimal(base_size = 15) +
  theme(
    axis.text.x = element_text(angle = 45, hjust = 1),
    plot.title = element_text(hjust = 0.5, face = "bold"),
    axis.title.x = element_text(face = "bold"),
    axis.title.y = element_text(face = "bold"),
    legend.position = "bottom",
    legend.title = element_text(face = "bold")
  )
```

```r
ggplot(data, aes(x = Unique_Period)) +
  geom_line(aes(y = Revenue_SA, color = "Revenue"), size = 1) +
  geom_line(aes(y = Expenditure_SA, color = "Expenditure"), size = 1) +
  labs(
    x = "Date ID",
    y = "Amount (? in millions)",
    title = "Revenue and Expenditure Over Time",
    color = "Legend"
  ) +
  scale_color_manual(values = c("Revenue" = "blue", "Expenditure" = "red")) +
  theme_minimal(base_size = 15) +
  theme(
    axis.text.x = element_text(angle = 45, hjust = 1),
    plot.title = element_text(hjust = 0.5, face = "bold"),
    axis.title.x = element_text(face = "bold"),
    axis.title.y = element_text(face = "bold"),
    legend.position = "bottom",
    legend.title = element_text(face = "bold")
  )



ggplot(data, aes(x = Unique_Period))+
  geom_line(aes(y = GDP, color = "GDP"), size = 1) +
  geom_line(aes(y = GDP_SA, color = "GDP_SA"), size = 1) +
  labs(
    x = "Date ID",
    y = "Amount (? in millions)",
    title = "Revenue and Expenditure Over Time",
    color = "Legend"
  ) +
  scale_color_manual(values = c("GDP" = "blue", "GDP_SA" = "red")) +
  theme_minimal(base_size = 15) +
  theme(
    axis.text.x = element_text(angle = 45, hjust = 1),
    plot.title = element_text(hjust = 0.5, face = "bold"),
    axis.title.x = element_text(face = "bold"),
    axis.title.y = element_text(face = "bold"),
    legend.position = "bottom",
    legend.title = element_text(face = "bold")
  )



ggplot(data, aes(x = Unique_Period)) +
```

```r
  geom_line(aes(y = Deflator, color = "Deflator"), size = 1) +
  labs(
    x = "Date ID",
    y = "Amount (? in millions)",
    title = "Revenue and Expenditure Over Time",
    color = "Legend"
  ) +
  scale_color_manual(values = c("Deflator" = "blue", "Expenditure" = "red")) +
  theme_minimal(base_size = 15) +
  theme(
    axis.text.x = element_text(angle = 45, hjust = 1),
    plot.title = element_text(hjust = 0.5, face = "bold"),
    axis.title.x = element_text(face = "bold"),
    axis.title.y = element_text(face = "bold"),
    legend.position = "bottom",
    legend.title = element_text(face = "bold")
  )
```

```r
clean_data <- na.omit(model_data)

tmp <- clean_data[,-1]

OptimalLag <-  VARselect(clean_data[,-c(1)], lag.max = 5, type = "const")
OptimalLag$selection
# OptimalLag$criteria

# library(vars)

# reduced_VAR <- VAR(clean_data[, -1], p = 4, type = "const")
reduced_VAR <- VAR(clean_data[, -1], p = 4)

# summary(reduced_VAR)

# Summary reports the roots of the polynomial.


# Define the 5 dimensional lower triangular matrix, A
```

```r
# Recover structural VAR using Cholesky decomposition
Amat <- matrix(c(1, 0, 0, 0, 0,   # Recursive ordering
                 NA, 1, 0, 0, 0,
                 NA, NA, 1, 0, 0,
                 NA, NA, NA, 1, 0,
                 NA, NA, NA, NA, 1),
               nrow = 5, byrow = TRUE)

svar_model <- SVAR(reduced_VAR, Amat = Amat, estmethod = "direct")
# ?SVAR()

structural_shocks <- residuals(svar_model)

svar_model

irf_result <- irf(svar_model, n.ahead = 10, ci = 0.9, boot = 500, cumulative = FALSE)  # Fo
# plot(irf_result)
# Visualize IRFs

FEVD_result <- fevd(svar_model, n.ahead = 10)  # Forecast horizons
plot(FEVD_result)

# Extract the first and second parts of the variable name
# Convert IRF results to data frames
irf_data <- as.data.frame(irf_result$irf)
irf_lower <- as.data.frame(irf_result$Lower)
irf_upper <- as.data.frame(irf_result$Upper)

# Add a time index to align data
irf_data$Time <- seq_len(nrow(irf_data))
irf_lower$Time <- irf_data$Time
irf_upper$Time <- irf_data$Time

# Reshape data for structured plotting
irf_long <- tidyr::pivot_longer(irf_data, cols = -Time, names_to = "Variable", values_to = '
lower_long <- tidyr::pivot_longer(irf_lower, cols = -Time, names_to = "Variable", values_to
upper_long <- tidyr::pivot_longer(irf_upper, cols = -Time, names_to = "Variable", values_to

# Merge confidence bounds into IRF dataset
irf_long <- irf_long %>%
  dplyr::left_join(lower_long, by = c("Time", "Variable")) %>%
  dplyr::left_join(upper_long, by = c("Time", "Variable")) %>%
  mutate(Shock = sub("\\..*", "", Variable),  # Extract part before dot
         Affected_Var = sub(".*\\.", "", Variable))  # Extract part after dot
```

```r
shock_names <- unique(irf_long$Shock)
#
for (shock in shock_names) {
  p <- ggplot(irf_long %>% filter(Shock == shock), aes(x = Time, y = IRF)) +
    geom_line(size = 1, color = "blue") +  # Keep all lines the same color
    geom_line(aes(y = Lower), linetype = "dashed", color = "gray") +
    geom_line(aes(y = Upper), linetype = "dashed", color = "gray") +
    geom_hline(yintercept = 0, color = "black", size = 1) +  # Thick black x-axis line at y
    facet_wrap(~ Affected_Var, scales = "free_y") +  # Create facets for affected variables
    theme_minimal() +
    labs(title = paste("Impulse Response for Shock:", shock),
         x = "Time",
         y = "Response")

  print(p)  # Print each figure separately
}









# structural_shocks <- residuals(svar_model)
# irf_result <- irf(svar_model, n.ahead = 10)  # Forecast horizons
# plot(irf_result)  # Visualize IRFs



# fevd_result <- fevd(svar_model, n.ahead = 10)
# plot(fevd_result)
```

References

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