The Macroeconomic Effects of Fiscal Adjusments in The UK $\,$

Samid Ali

Contents

1	Introduction	2
2	Identification	4
3	Recovering Structural Shocks	5
4	References	7
5	Technical Appendix	8

Introduction

Sutherland, Hoeller, and Merola (Sutherland, Hoeller, and Merola [5]) 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. Warmedinger, Checherita-Westphal, and de Cos (Warmedinger, Checherita-Westphal, and De Cos [6]) 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. Therefore, fiscal consolidation is clearly needed to ensure the long-term resilience of the economy. As a target, Sutherland, Hoeller, and Merola (Sutherland, Hoeller, and Merola [5]) 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. 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.

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 (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. 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 mul-

tipliers to understand potential trade-offs between various economic objectives. Ilzetzki, Mendoza, and Vegh (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.

To achieve this objective, this research will use a Structural Vector Autoregressive (VAR) model to estimate the fiscal multiplier. As a baseline, a three-dimensional VAR is proposed: featuring government revenue, government expenditure, and output. It should be noted that there are several definitions for the fiscal variables used in the literature. Blanchard and Perotti (2002) note that the choice of fiscal variables reflects "theoretical priors." Therefore, the definitions of the fiscal variables used will need to be clearly articulated, determined based on data availability and explicit economic assumptions. Regarding identification for the structural VAR, Mountford and Uhlig (Mountford and Uhlig [4]) provide convincing economic rationale for sign restrictions on the impulse responses. This strategy imposes fewer restrictions on the model and is thus more robust to misspecification. However, this approach also has drawbacks, as it means that the parameters will only be set identified. Thus, further work may be required to pin down the structural impulse responses (Kilian and Lütkepohl [3]). # Data

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

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)

```
## Classes 'data.table' and 'data.frame': 152 obs. of 6 variables:
## $ CDID : chr "1987 Q1" "1987 Q2" "1987 Q3" "1987 Q4" ...
## $ Deflator: num 34.8 35.3 36 36.3 36.7 ...
## $ GDP : num 314804 319478 327346 331075 336442 ...
## $ Year : num 1987 1987 1987 1988 ...
## $ Quarter : chr "Q1" "Q2" "Q3" "Q4" ...
## $ Q : num 1 2 3 4 1 2 3 4 1 2 ...
## - attr(*, ".internal.selfref")=<externalptr>
## `summarise()` has grouped output by 'Year'. You can override using the ".groups` argument.
```

Identification:

Recovering Structural Shocks

Let Y_t be the vector of variables:

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

The reduced-form VAR model can be written as:

$$Y_t = A_1Y_{t-1} + A_2Y_{t-2} + \cdots + A_pY_{t-p} + \epsilon_t$$

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

$$\epsilon_t = Bu_t$$

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 \boldsymbol{u}_t can be recovered as:

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

References

Blanchard, O.J. and Leigh, D., 2013. Growth forecast errors and fiscal multipliers. American Economic Review, 103(3), pp.117-120.

Caldara, D. and Kamps, C., 2008. What are the effects of fiscal policy shocks? A VAR-based comparative analysis.

Caldara, D. and Kamps, C., 2017. The analytics of SVARs: a unified framework to measure fiscal multipliers. The Review of Economic Studies, 84(3), pp.1015-1040.

Ilzetzki, E., Mendoza, E.G. and Végh, C.A., 2013. How big (small?) are fiscal multipliers?. Journal of monetary economics, 60(2), pp.239-254. Kilian, L. and Lütkepohl, H., 2017. Structural vector autoregressive analysis. Cambridge University Press. Mountford, A. and Uhlig, H., 2009. What are the effects of fiscal policy shocks?. Journal of applied econometrics, 24(6), pp.960-992. Sutherland, D., Hoeller, P. and Merola, R., 2012. Fiscal consolidation: How much, how fast and by what means?. Warmedinger, T., Checherita-Westphal, C.D. and De Cos, P.H., 2015. Fiscal multipliers and beyond. ECB Occasional Paper, 162.

Technical Appendix

```
library(ggplot2)
library(knitr)
library(ivreg)
library(ggdag)
library(data.table)
library(dplyr)
library(tidyr)
library(stargazer)
library(clipr)
library(tibble)
library(lubridate)
#library(kableExtra)
knitr::opts_chunk$set(echo = FALSE)
df <- fread("D:/Samid work/University/KCL - Econ and Policy/Dissertation/Data/GDP.csv", skij
# Filter the data frame to exclude rows where the column 'title' matches any of the specifi
filtered_df <- df %>%
  # Only keep the quarterly data
  subset(nchar(CDID) == 7 & substr(CDID,6,6) == "Q") %>%
  select(CDID,Deflator = L8GG, GDP = ABMI) %>%
  mutate(Year = as.numeric(substr(CDID,1,4)),
         Quarter = substr(CDID, 6, 7),
         Q = as.numeric(substr(CDID,7,7))) %>%
```

```
# For testing purposes, can change later
     subset(Year >= 1987) %>%
    mutate(Deflator = as.numeric(Deflator),
                       GDP = as.numeric(GDP))
# View the filtered data frame
# head(filtered_df)
str(filtered_df)
# L8GG
fiscal_raw <- fread("D:/Samid work/University/KCL - Econ and Policy/Dissertation/Data/Fiscal
fiscal_proc <- fiscal_raw %>%
     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/Population - Fread("D:/Samid work/University/KCL - Econ and Policy/Dissertation/Data/Population/Data/Population/Data/Population/Data/Population/Data/Population/Data/Population/Data/Population/Data/Population/Data/Population/Data/Population/Data/Population/Data/Population/Data/Population/Data/Population/Data/Population/Data/Population/Data/Population/Data/Population/Data/Population/Data/Population/Data/Population/Data/Population/Data/Population/Data/Population/Data/Population/Data/Population/Data/Population/Data/Population/Data/Population/Data/Population/Data/Population/Data/Population/Data/Population/Data/Population/Data/Population/Data/Population/Data/Population/Data/Population/Data/Population/Data/Population/Data/Population/Data/Population/Data/Population/Data/Population/Data/Population/Data/Population/Data/Population/Data/Population/Data/Population/Data/Population/Data/Population/Data/Population/Data/Population/Data/Population/Data/Population/Data/Population/Data/Population/Data/Population/Data/Population/D
                                                     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</pre>
  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))
data <- fiscal_proc %>%
  left_join(filtered_df, by = c("Q" = "Q", "Year" = "Year")) %>%
  left_join(Interest_SR, 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 oldsymbol{	extit{f}} million so n
  mutate(RevenuePerCapita = (Revenue *10^6) /Population,
         ExpenditurePerCapita = (Expenditure *10^6) /Population,
         GDPPerCapita = (GDP *10^6) /Population) %>%
# Convert variables (except interest rate) to logs
  mutate(log_revenue = log(Revenue *10^6),
         log_expenditure = log(Expenditure *10^6),
         log_GDP = log(GDP *10^6),
         log_deflator = log(Deflator))
model_data <- data %>%
  select(CDID, log_revenue, log_expenditure, log_GDP, log_deflator, mean_SR_Rate)
\# ggplot(fiscal\_proc, aes(x = Year2)) +
   geom_line(aes(y = Revenue, color = "Revenue"), size = 1) +
    qeom_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")
```

Bibliography

- [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] L. Kilian and H. Lütkepohl. Structural vector autoregressive analysis. Cambridge University Press, 2017.
- [4] A. Mountford and H. Uhlig. "What are the effects of fiscal policy shocks?" In: *Journal of Applied Econometrics* 24.6 (2009), pp. 960–992.
- [5] D. Sutherland, P. Hoeller, and R. Merola. "Fiscal consolidation: How much, how fast and by what means?" In: (2012).
- [6] T. Warmedinger, C.D. Checherita-Westphal, and P.H. De Cos. "Fiscal multipliers and beyond". In: *ECB Occasional Paper* 162 (2015).