

favar_sdfm

laura montaldo

2023-11-04

```
library(Metrics)
library(forecast)

## Registered S3 method overwritten by 'quantmod':
##   method      from
##   as.zoo.data.frame zoo

##
## Attaching package: 'forecast'

## The following object is masked from 'package:Metrics':
##
##   accuracy

library(readxl)
library(readr)
library(boot)
library(tsDyn)

##
## Attaching package: 'tsDyn'

## The following object is masked from 'package:Metrics':
##
##   mse

library(vars)

## Loading required package: MASS
## Loading required package: strucchange
## Loading required package: zoo

##
## Attaching package: 'zoo'

## The following objects are masked from 'package:base':
##
##   as.Date, as.Date.numeric

## Loading required package: sandwich
## Loading required package: urca
## Loading required package: lmtest

library(repr)
library(dplyr)
```

```

##
## Attaching package: 'dplyr'

## The following object is masked from 'package:MASS':
##
##     select

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

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

library(dfms)
library(xts)

##
## ##### Warning from 'xts' package #####
## #
## # The dplyr lag() function breaks how base R's lag() function is supposed to #
## # work, which breaks lag(my_xts). Calls to lag(my_xts) that you type or #
## # source() into this session won't work correctly. #
## #
## # Use stats::lag() to make sure you're not using dplyr::lag(), or you can add #
## # conflictRules('dplyr', exclude = 'lag') to your .Rprofile to stop #
## # dplyr from breaking base R's lag() function. #
## #
## # Code in packages is not affected. It's protected by R's namespace mechanism #
## # Set `options(xts.warn_dplyr_breaks_lag = FALSE)` to suppress this warning. #
## #
## #####
##
## Attaching package: 'xts'

## The following objects are masked from 'package:dplyr':
##
##     first, last

library(vars)
library(fbi)
library(forecast)
library(OOS)
library(zoo)

cat("My Working directory is: ", getwd(), "\n")

## My Working directory is: C:/Users/user/Desktop/Tesis_Maestria/src/stage2_models

df_train <- read_csv("../data/prepro/sfr_train.csv", show_col_types = FALSE)
df_test <- read_csv("../data/prepro/sfr_test.csv", show_col_types = FALSE)
slow <- read_csv("../data/prepro/slow_columns.csv", show_col_types = FALSE)
fast <- read_csv("../data/prepro/fast_columns.csv", show_col_types = FALSE)
descr <- read.table("../data/prepro/descripciones.txt", header = TRUE, sep = "\t")

```

Dataframe a objeto xts

```
df=df_train
# Convert the date_column to Date type
df$index <- as.Date(df$index)
# Create an xts object with the date_column as the index
xts_object <- xts(df[, -which(colnames(df) == "index")], order.by = df$index)
cat("Rango de datos:", as.character(range(index(xts_object))), "\n")

## Rango de datos: 1960-01-01 2008-01-01

data_s = scale(xts_object, center = TRUE, scale = TRUE)
cat("Tamaño de mi muestra:", dim(data_s), "\n")
```

```
## Tamaño de mi muestra: 577 121
```

Paso 1: se extraen los componentes principales de X_t incluyendo Y_t y se determina la cantidad óptima de factores

```
ics = ICr(data_s)
ic_p2_factors=ics$r.star[2]
print(ics)

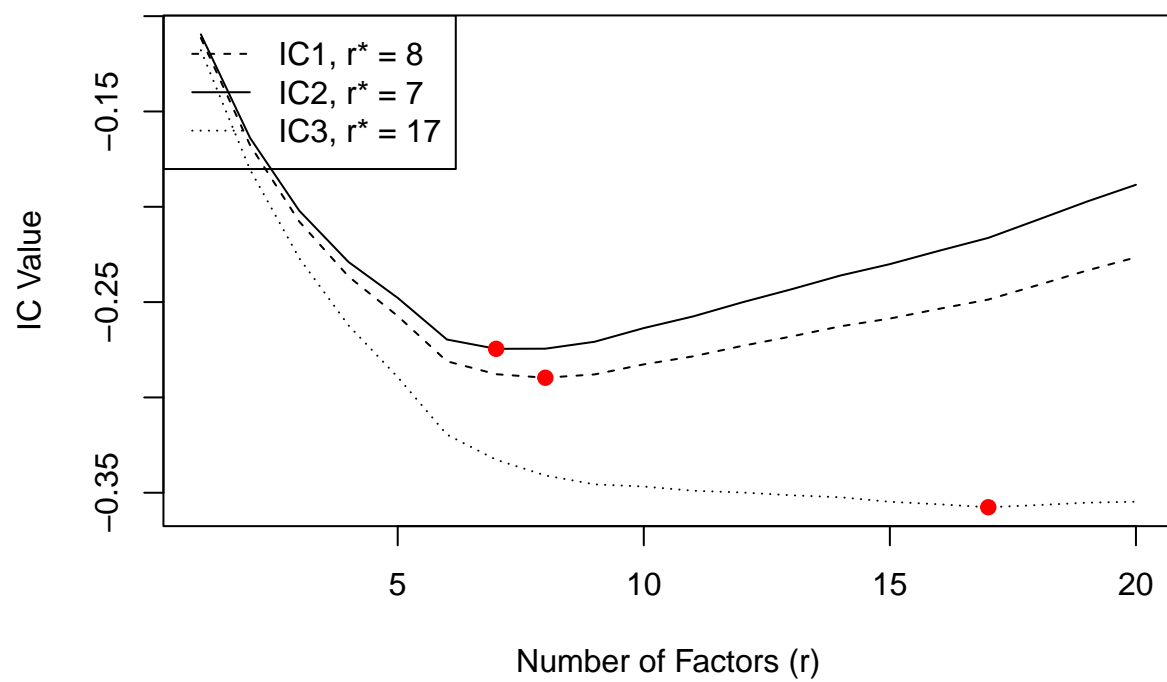
## Optimal Number of Factors (r) from Bai and Ng (2002) Criteria
##
## IC1 IC2 IC3
## 8 7 17

dim(ics$F_pca)

## [1] 577 121

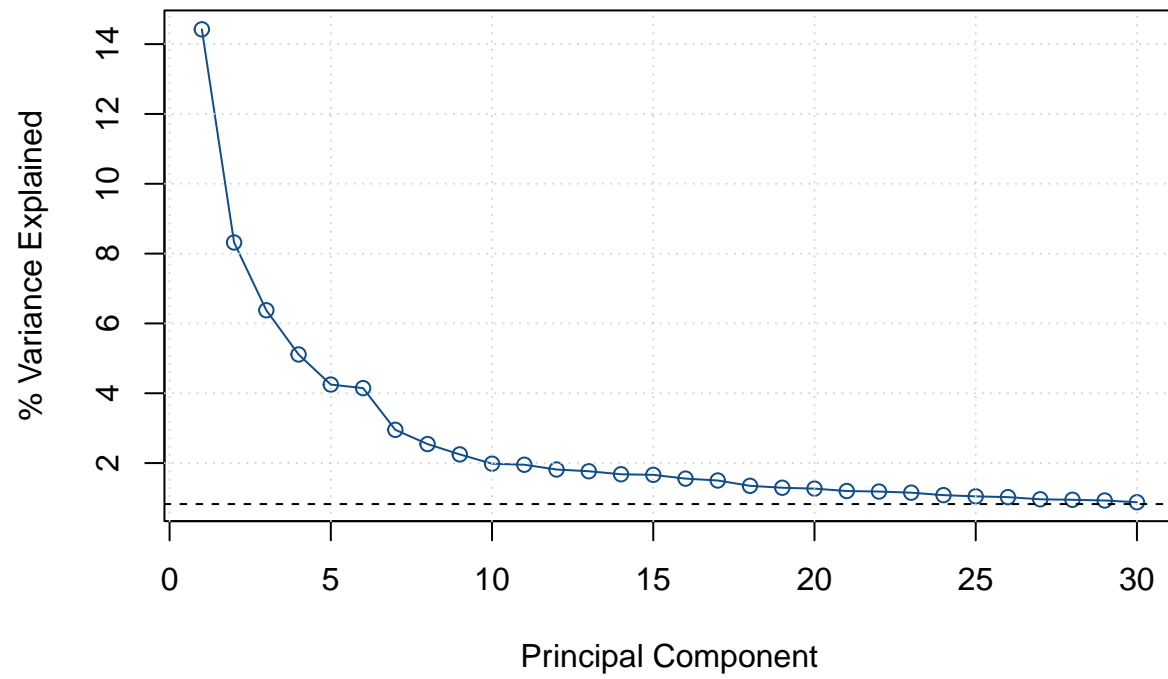
plot(ics)
```

Optimal Number of Factors (r) from Bai and Ng (2002) Criteria



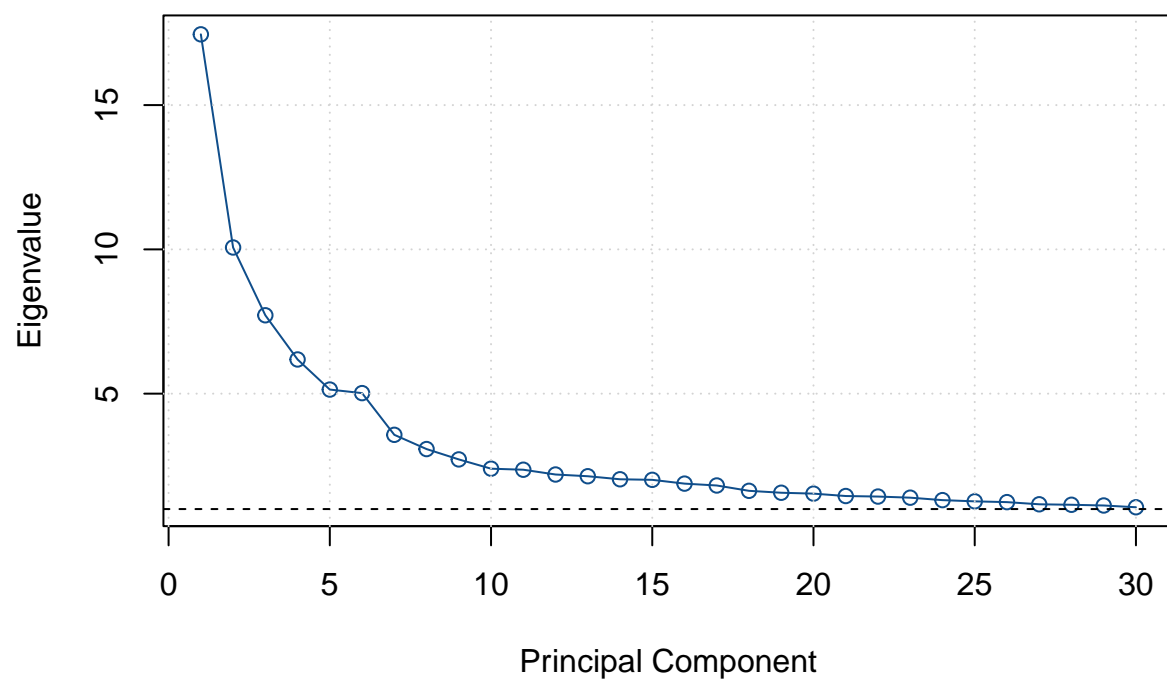
```
screepplot(ics, main="Scree plot")
```

Scree plot



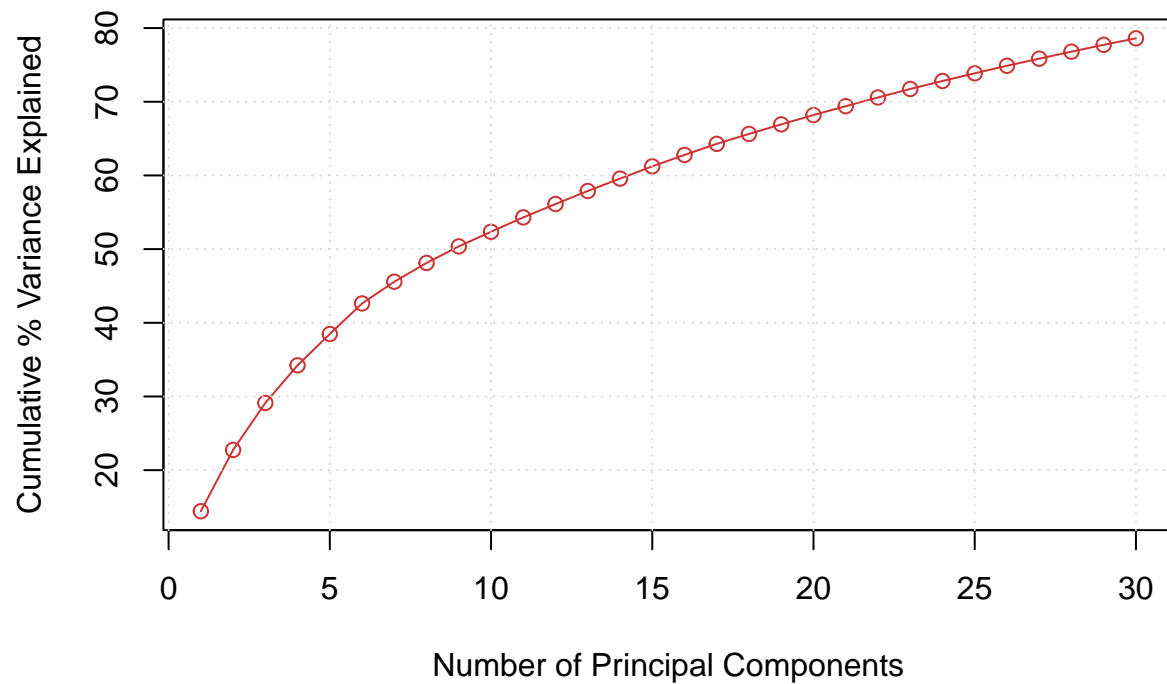
```
screeplot(ics, type="ev", main="Scree plot")
```

Scree plot



```
screeplot(ics,type="cum.pve", main="Scree plot")
```

Scree plot



```
# components all
C<-ics$F_pca[, 1:ic_p2_factors]
cat("Dimensiones de los factores comunes en filas y columnas:", dim(C))
```

```
## Dimensiones de los factores comunes en filas y columnas: 577 7
```

Paso 2: se extraen los componentes principales de las variables lentas

```
slow_vars <- unlist(slow$slow)
data_slow <- data_s[, slow_vars]
```

```
cat("Dimensiones de los factores de las variables lentas:", dim(data_slow))
```

```
## Dimensiones de los factores de las variables lentas: 577 72
```

```
ics_slow = ICr(data_slow)
ic_p2_slow_factors=ics_slow$r.star[2]
```

```
print(ics_slow)
```

```
## Optimal Number of Factors (r) from Bai and Ng (2002) Criteria
```

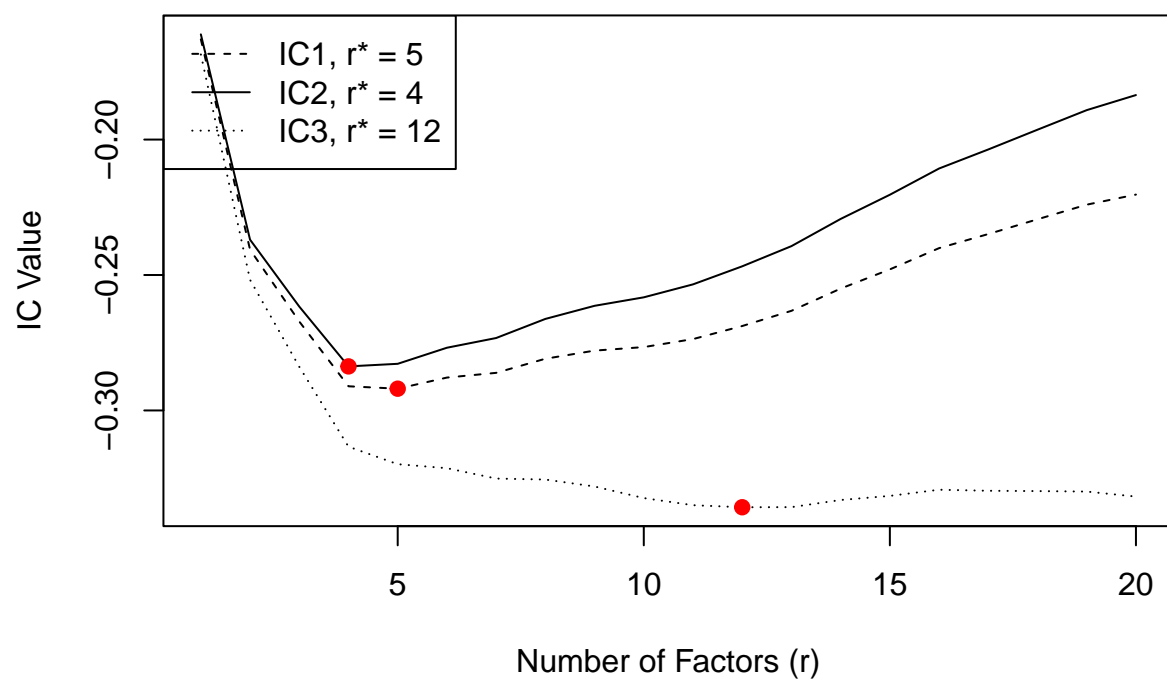
```
##
```

```
## IC1 IC2 IC3
```

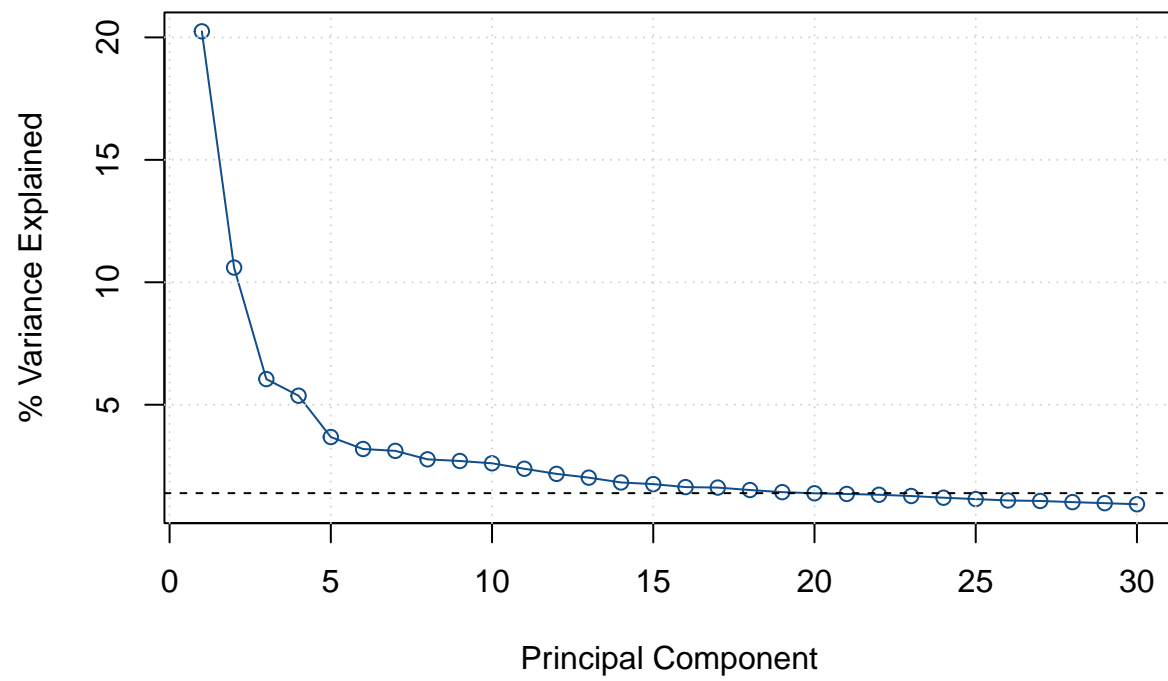
```
## 5 4 12
```

```
plot(ics_slow)
```

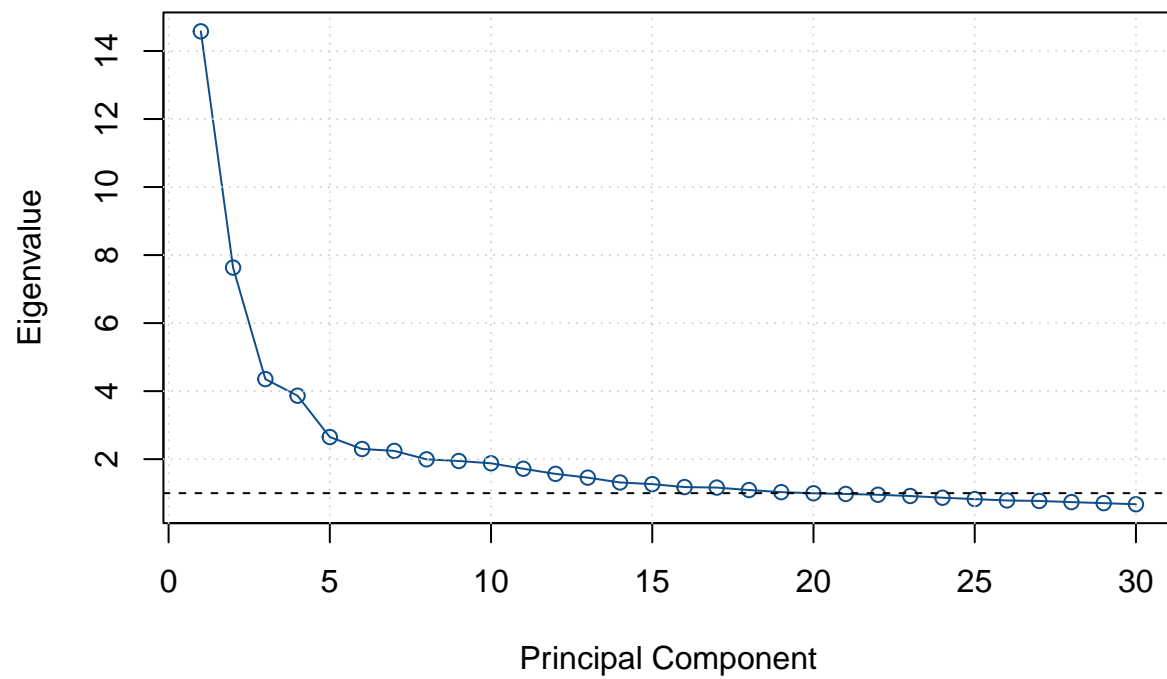
Optimal Number of Factors (r) from Bai and Ng (2002) Criteria



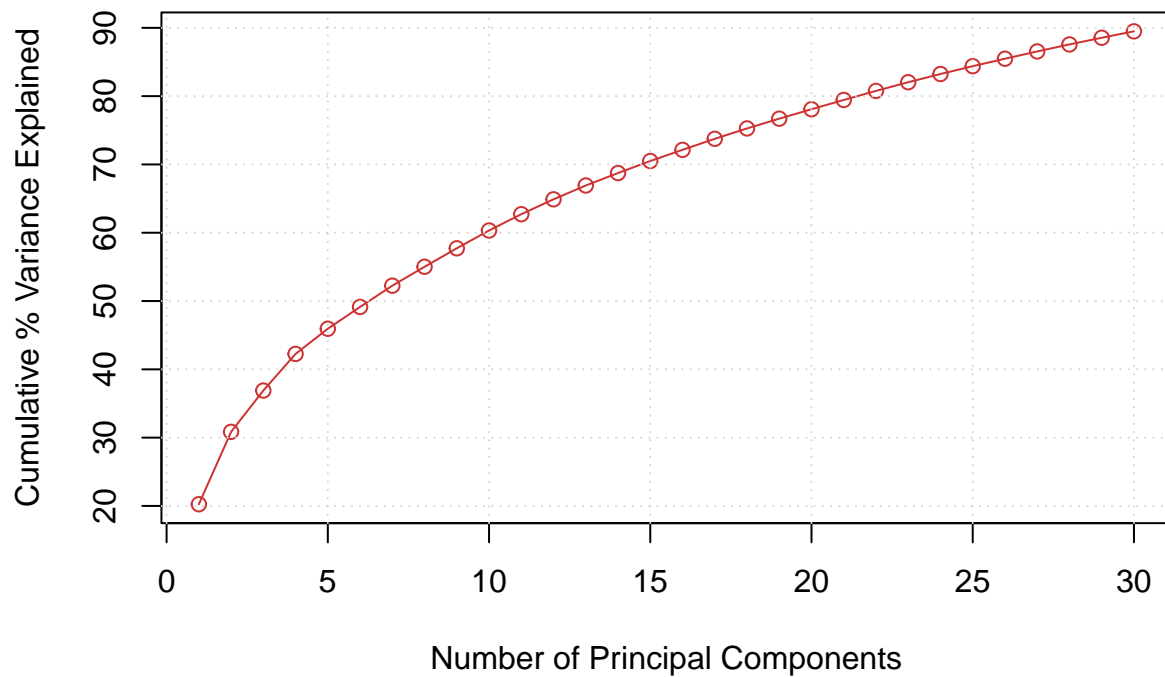
```
screepplot(ics_slow)
```

```
screeplot(ics_slow, type="ev")
```



```
screeplot(ics_slow,type="cum.pve")
```



```
F_slow<-ics$F_pca[,1:ic_p2_slow_factors]
dim(F_slow)
```

```
## [1] 577 4
```

```
dim(C)
```

```
## [1] 577 7
```

Step 3: Se limpian a los CP de los efectos de Y (FEDFUNDS)

```
fedfunds <- as.matrix(data_s[, "FEDFUNDS"])
reg <- lm(C ~ F_slow + fedfunds)
```

\hat{F}_t

```
F_hat <- C - data.matrix(data_s[, "FEDFUNDS"]) %*% reg$coefficients[nrow(reg$coefficients),]
dim(F_hat)
```

```
## [1] 577 7
```

Step 4: Estimo el FAVAR y las funciones de impulso-respuesta

```
data_var <- data.frame(F_hat, "FEDFUNDS" = data_s[, "FEDFUNDS"])
head(data_var)# common components
```

```
##          PC1          PC2          PC3          PC4          PC5          PC6
```

```
## 1960-01-01 -7.4735326 -0.8138485 -2.6455136 -2.6365323 -5.1851192 -4.99703466
## 1960-02-01 0.2607595 2.8427705 0.7051430 -0.8325004 3.4964146 -1.86783561
## 1960-03-01 9.1145991 1.2271706 0.3890168 -1.7147965 -0.8151777 -2.89462563
## 1960-04-01 -1.8575241 0.4373753 1.6077299 3.7789511 2.5329622 0.09713551
## 1960-05-01 5.6978743 0.9456075 -1.8653719 -4.0243107 -1.9859044 0.80783573
## 1960-06-01 8.3183110 -2.8597768 0.1585260 0.4133536 0.2651923 0.98907113
##
##          PC7      FEDFUNDS
## 1960-01-01 1.616118 0.01130991
## 1960-02-01 -4.871665 -0.04291257
## 1960-03-01 -3.234759 -0.34113620
## 1960-04-01 -7.915231 0.22819983
## 1960-05-01 3.575720 -0.17846876
## 1960-06-01 -1.816141 -1.42558579
```

```
var_select <- VARselect(data_var, lag.max = 15, type="none")
```

```
best_lag <- var_select$selection
best_lag[1]
```

```
## AIC(n)
##      6
```

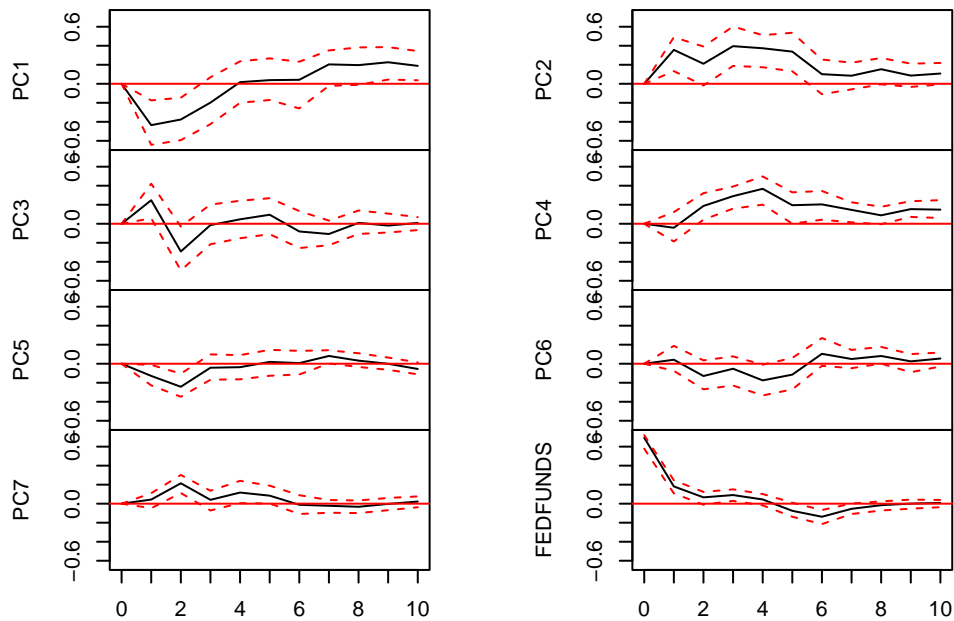
```
cat("Best # lags according to AIC:", best_lag[1], "\n")
```

```
## Best # lags according to AIC: 6
```

```
var = VAR(data_var, p =best_lag[1])
```

```
irf_results <- irf(var, impulse = "FEDFUNDS", n.ahead = 10)
plot(irf_results)
```

Orthogonal Impulse Response from FEDFUNDS



95 % Bootstrap CI, 100 runs

```
irf_point = irf(var, n.ahead = 48, impulse = "FEDFUNDS", response = "FEDFUNDS", boot = FALSE)
# Shock size of 25 basis points
impulse_sd = 0.25/sd(df$FEDFUNDS)
scale = impulse_sd/(irf_point$irf$FEDFUNDS[1]) # position of FYFF response at step 0
```

```
# Computing Loading Factors
matriz_s<- as.matrix(data_s)
matriz_fhat<- as.matrix(F_hat)
reg_loadings = lm(matriz_s ~ 0 + matriz_fhat + data_s[, "FEDFUNDS"])
loadings = reg_loadings$coefficients
#head(reg_loadings$coefficients)
#summary(reg_loadings)
Lamda_F=loadings[1:7,]
Lambda_ffr=loadings[nrow(loadings),]
```

```
#### BOOTSTRAPING ####
R = 500 # Number of simulations
nvars = dim(data_s)[2] # Number of variables
nsteps = 49 # numbers of steps
IRFs = array(c(0,0,0), dim = c(nsteps,nvars,R))
var = lineVar(data_var, lag = best_lag[1], include = "const")
for(j in 1:R){
  data_boot = VAR.boot(var, boot.scheme = "resample")
  var_boot = VAR(data_boot, lag = best_lag[1])
  irf1 = irf(var_boot, n.ahead = 48, impulse = "FEDFUNDS", boot = FALSE)
  for(i in 1:nvars){
    IRFs[,i,j] = (irf1$irf$FEDFUNDS %*% matrix(loadings[, i]))*scale
```

```

    }
} ## Boot simulations done

# Extract the quantiles of IRFs we are interested: 90% confidence intervals in BBE
Upper = array(c(0,0), dim = c(nsteps, nvars))
for(k in 1:nsteps){
  for(i in 1:nvars){
    Upper[k,i] = quantile(IRFs[k,i,], probs = c(0.95))[1]
  }
}
Lower = array(c(0,0), dim = c(nsteps, nvars))
for(k in 1:nsteps){
  for(i in 1:nvars){
    Lower[k,i] = quantile(IRFs[k,i,], probs = c(0.05))[1]
  }
}
IRF = array(c(0,0), dim = c(nsteps, nvars))
for(k in 1:nsteps){
  for(i in 1:nvars){
    IRF[k,i] = quantile(IRFs[k,i,], probs = c(0.5))[1]
  }
}
rm(var_boot)
rm(IRFs)

```

```

matching_names <- intersect(names(data_s), descr$fred)
filtered_descr <- descr %>%filter(fred %in% matching_names)
filtered_descr

```

##	fred	description
## 1	RPI	Real Personal Income
## 2	W875RX1	Real personal income ex transfer receipts
## 3	DPCERA3M086SBEA	Real personal consumption expenditures
## 4	CMRMTSPLx	Real Manu. and Trade Industries Sales
## 5	RETAILx	Retail and Food Services Sales
## 6	INDPRO	IP Index
## 7	IPFPNSS	IP: Final Products and Nonindustrial Supplies
## 8	IPFINAL	IP: Final Products (Market Group)
## 9	IPCONGD	IP: Consumer Goods
## 10	IPDCONGD	IP: Durable Consumer Goods
## 11	IPNCONGD	IP: Nondurable Consumer Goods
## 12	IPBUSEQ	IP: Business Equipment
## 13	IPMAT	IP: Materials
## 14	IPDMAT	IP: Durable Materials
## 15	IPNMAT	IP: Nondurable Materials
## 16	IPMANSICS	IP: Manufacturing (SIC)
## 17	IPB51222s	IP: Residential Utilities
## 18	IPFUELS	IP: Fuels
## 19	CUMFNS	Capacity Utilization: Manufacturing
## 20	HWI	Help-Wanted Index for United States
## 21	HWIURATIO	Ratio of Help Wanted/No. Unemployed
## 22	CLF160V	Civilian Labor Force
## 23	CE160V	Civilian Employment
## 24	UNRATE	Civilian Unemployment Rate

## 25	UEMPMEAN	Average Duration of Unemployment (Weeks)
## 26	UEMPLT5	Civilians Unemployed - Less Than 5 Weeks
## 27	UEMP5T014	Civilians Unemployed for 5-14 Weeks
## 28	UEMP150V	Civilians Unemployed - 15 Weeks & Over
## 29	UEMP15T26	Civilians Unemployed for 15-26 Weeks
## 30	UEMP270V	Civilians Unemployed for 27 Weeks and Over
## 31	CLAIMSx	Initial Claims
## 32	PAYEMS	All Employees: Total nonfarm
## 33	USGOOD	All Employees: Goods-Producing Industries
## 34	CES1021000001	All Employees: Mining and Logging: Mining
## 35	USCONS	All Employees: Construction
## 36	MANEMP	All Employees: Manufacturing
## 37	DMANEMP	All Employees: Durable goods
## 38	NDMANEMP	All Employees: Nondurable goods
## 39	SRVPRD	All Employees: Service-Providing Industries
## 40	USTPU	All Employees: Trade, Transportation & Utilities
## 41	USWTRADE	All Employees: Wholesale Trade
## 42	USTRADE	All Employees: Retail Trade
## 43	USFIRE	All Employees: Financial Activities
## 44	USGOVT	All Employees: Government
## 45	CES0600000007	Avg Weekly Hours : Goods-Producing
## 46	AWOTMAN	Avg Weekly Overtime Hours : Manufacturing
## 47	AWHMAN	Avg Weekly Hours : Manufacturing
## 48	HOUST	Housing Starts: Total New Privately Owned
## 49	HOUSTW	Housing Starts, West
## 50	PERMIT	New Private Housing Permits (SAAR)
## 51	PERMITNE	New Private Housing Permits, Northeast (SAAR)
## 52	PERMITS	New Private Housing Permits, South (SAAR)
## 53	PERMITW	New Private Housing Permits, West (SAAR)
## 54	AMDMNOx	New Orders for Durable Goods
## 55	AMDMUOx	Un lled Orders for Durable Goods
## 56	BUSINVx	Total Business Inventories
## 57	ISRATIOx	Total Business: Inventories to Sales Ratio
## 58	M1SL	M1 Money Stock
## 59	M2SL	M2 Money Stock
## 60	M2REAL	Real M2 Money Stock
## 61	TOTRESNS	Total Reserves of Depository Institutions
## 62	NONBORRES	Reserves Of Depository Institutions
## 63	BUSLOANS	Commercial and Industrial Loans
## 64	REALLN	Real Estate Loans at All Commercial Banks
## 65	NONREVSL	Total Nonrevolving Credit
## 66	CONSPI	Nonrevolving consumer credit to Personal Income
## 67	FEDFUNDS	E?ective Federal Funds Rate
## 68	CP3Mx	3-Month AA Financial Commercial Paper Rate
## 69	TB3MS	3-Month Treasury Bill:
## 70	TB6MS	6-Month Treasury Bill:
## 71	GS1	1-Year Treasury Rate
## 72	GS5	5-Year Treasury Rate
## 73	GS10	10-Year Treasury Rate
## 74	AAA	Moody s Seasoned Aaa Corporate Bond Yield
## 75	BAA	Moody s Seasoned Baa Corporate Bond Yield
## 76	COMPAPFFx	3-Month Commercial Paper Minus FEDFUNDS
## 77	TB3SMFFM	3-Month Treasury C Minus FEDFUNDS
## 78	TB6SMFFM	6-Month Treasury C Minus FEDFUNDS

## 79	T1YFFM	1-Year Treasury C Minus FEDFUNDS
## 80	T5YFFM	5-Year Treasury C Minus FEDFUNDS
## 81	T10YFFM	10-Year Treasury C Minus FEDFUNDS
## 82	AAAFFM	Moody s Aaa Corporate Bond Minus FEDFUNDS
## 83	BAAFFM	Moody s Baa Corporate Bond Minus FEDFUNDS
## 84	EXSZUSx	Switzerland / U.S. Foreign Exchange Rate
## 85	EXJPUSx	Japan / U.S. Foreign Exchange Rate
## 86	EXUSUKx	U.S. / U.K. Foreign Exchange Rate
## 87	EXCAUSx	Canada / U.S. Foreign Exchange Rate
## 88	WPSFD49207	PPI: Finished Goods
## 89	WPSFD49502	PPI: Finished Consumer Goods
## 90	WPSID61	PPI: Intermediate Materials
## 91	WPSID62	PPI: Crude Materials
## 92	OILPRICEx	Crude Oil, spliced WTI and Cushing
## 93	PPICMM	PPI: Metals and metal products:
## 94	CPIAUCSL	CPI : All Items
## 95	CPIAPPSL	CPI : Apparel
## 96	CPITRNSL	CPI : Transportation
## 97	CPIMEDSL	CPI : Medical Care
## 98	CUSR0000SAC	CPI : Commodities
## 99	CUSR0000SAD	CPI : Durables
## 100	CUSR0000SAS	CPI : Services
## 101	CPIULFSL	CPI : All Items Less Food
## 102	CUSR0000SAOL2	CPI : All items less shelter
## 103	CUSR0000SAOL5	CPI : All items less medical care
## 104	PCEPI	Personal Cons. Expend.: Chain Index
## 105	DDURRG3M086SBEA	Personal Cons. Exp: Durable goods
## 106	DNDGRG3M086SBEA	Personal Cons. Exp: Nondurable goods
## 107	DSERRG3M086SBEA	Personal Cons. Exp: Services
## 108	CES06000000008	Avg Hourly Earnings : Goods-Producing
## 109	CES20000000008	Avg Hourly Earnings : Construction
## 110	CES30000000008	Avg Hourly Earnings : Manufacturing
## 111	DTCOLNVHFNM	Consumer Motor Vehicle Loans Outstanding
## 112	DTCTHFNM	Total Consumer Loans and Leases Outstanding
## 113	INVEST	Securities in Bank Credit at All Commercial Banks
##	gsi.description	group slow_1_fast_0
## 1	PI	Output and Income 1
## 2	PI less transfers	Output and Income 1
## 3	Real Consumption	Consumption, Orders, and Inventories 1
## 4	M&T sales	Consumption, Orders, and Inventories 0
## 5	Retail sales	Consumption, Orders, and Inventories 0
## 6	IP: total	Output and Income 1
## 7	IP: products	Output and Income 1
## 8	IP: nal prod	Output and Income 1
## 9	IP: cons gds	Output and Income 1
## 10	IP: cons dble	Output and Income 1
## 11	IP: cons nondble	Output and Income 1
## 12	IP: bus eqpt	Output and Income 1
## 13	IP: matls	Output and Income 1
## 14	IP: dble matls	Output and Income 1
## 15	IP: nondble matls	Output and Income 1
## 16	IP: mfg	Output and Income 1
## 17	IP: res util	Output and Income 1
## 18	IP: fuels	Output and Income 1

## 19	Cap util	Output and Income	1
## 20	Help wanted indx	Labor Market	1
## 21	Help wanted/unemp	Labor Market	1
## 22	Emp CPS total	Labor Market	1
## 23	Emp CPS nonag	Labor Market	1
## 24	U: all	Labor Market	1
## 25	U: mean duration	Labor Market	1
## 26	U < 5 wks	Labor Market	1
## 27	U 5-14 wks	Labor Market	1
## 28	U 15+ wks	Labor Market	1
## 29	U 15-26 wks	Labor Market	1
## 30	U 27+ wks	Labor Market	1
## 31	UI claims	Labor Market	1
## 32	Emp: total	Labor Market	1
## 33	Emp: gds prod	Labor Market	1
## 34	Emp: mining	Labor Market	1
## 35	Emp: const	Labor Market	1
## 36	Emp: mfg	Labor Market	1
## 37	Emp: dble gds	Labor Market	1
## 38	Emp: nondbles	Labor Market	1
## 39	Emp: services	Labor Market	1
## 40	Emp: TTU	Labor Market	1
## 41	Emp: wholesale	Labor Market	1
## 42	Emp: retail	Labor Market	1
## 43	Emp: FIRE	Labor Market	1
## 44	Emp: Govt	Labor Market	1
## 45	Avg hrs	Labor Market	1
## 46	Overtime: mfg	Labor Market	1
## 47	Avg hrs: mfg	Labor Market	1
## 48	Starts: nonfarm	Housing	0
## 49	Starts: West	Housing	0
## 50	BP: total	Housing	0
## 51	BP: NE	Housing	0
## 52	BP: South	Housing	0
## 53	BP: West	Housing	0
## 54	Orders: dble gds	Consumption, Orders, and Inventories	0
## 55	Unf orders: dble	Consumption, Orders, and Inventories	0
## 56	M&T invent	Consumption, Orders, and Inventories	0
## 57	M&T invent/sales	Consumption, Orders, and Inventories	0
## 58	M1	Money and Credit	0
## 59	M2	Money and Credit	0
## 60	M2 (real)	Money and Credit	0
## 61	Reserves tot	Money and Credit	0
## 62	Reserves nonbor	Money and Credit	0
## 63	C&I loan plus	Money and Credit	0
## 64	DC&I loans	Money and Credit	0
## 65	Cons credit	Money and Credit	0
## 66	Inst cred/PI	Money and Credit	0
## 67	Fed Funds	Interest and Exchange Rates	0
## 68	Comm paper	Interest and Exchange Rates	0
## 69	3 mo T-bill	Interest and Exchange Rates	0
## 70	6 mo T-bill	Interest and Exchange Rates	0
## 71	1 yr T-bond	Interest and Exchange Rates	0
## 72	5 yr T-bond	Interest and Exchange Rates	0

## 73	10 yr T-bond	Interest and Exchange Rates	0
## 74	Aaa bond	Interest and Exchange Rates	0
## 75	Baa bond	Interest and Exchange Rates	0
## 76	CP-FF spread	Interest and Exchange Rates	0
## 77	3 mo-FF spread	Interest and Exchange Rates	0
## 78	6 mo-FF spread	Interest and Exchange Rates	0
## 79	1 yr-FF spread	Interest and Exchange Rates	0
## 80	5 yr-FF spread	Interest and Exchange Rates	0
## 81	10 yr-FF spread	Interest and Exchange Rates	0
## 82	Aaa-FF spread	Interest and Exchange Rates	0
## 83	Baa-FF spread	Interest and Exchange Rates	0
## 84	Ex rate: Switz	Interest and Exchange Rates	0
## 85	Ex rate: Japan	Interest and Exchange Rates	0
## 86	Ex rate: UK	Interest and Exchange Rates	0
## 87	EX rate: Canada	Interest and Exchange Rates	0
## 88	PPI: n gds	Prices	1
## 89	PPI: cons gds	Prices	1
## 90	PPI: int matls	Prices	1
## 91	PPI: crude matls	Prices	1
## 92	Spot market price	Prices	1
## 93	PPI: nonferrous	Prices	1
## 94	CPI-U: all	Prices	1
## 95	CPI-U: apparel	Prices	1
## 96	CPI-U: transp	Prices	1
## 97	CPI-U: medical	Prices	1
## 98	CPI-U: comm.	Prices	1
## 99	CPI-U: dbles	Prices	1
## 100	CPI-U: services	Prices	1
## 101	CPI-U: ex food	Prices	1
## 102	CPI-U: ex shelter	Prices	1
## 103	CPI-U: ex med	Prices	1
## 104	PCE de	Prices	1
## 105	PCE de : dlbes	Prices	1
## 106	PCE de : nondble	Prices	1
## 107	PCE de : service	Prices	1
## 108	AHE: goods	Labor Market	1
## 109	AHE: const	Labor Market	1
## 110	AHE: mfg	Labor Market	1
## 111	<NA>	Money and Credit	0
## 112	<NA>	Money and Credit	0
## 113	<NA>	Money and Credit	0
##	drop_aggregate_1 X X.1 X.2		
## 1	0 NA NA NA		
## 2	0 NA NA NA		
## 3	0 NA NA NA		
## 4	0 NA NA NA		
## 5	0 NA NA NA		
## 6	1 NA NA NA		
## 7	0 NA NA NA		
## 8	0 NA NA NA		
## 9	0 NA NA NA		
## 10	0 NA NA NA		
## 11	0 NA NA NA		
## 12	0 NA NA NA		

## 13	0 NA NA NA
## 14	0 NA NA NA
## 15	0 NA NA NA
## 16	0 NA NA NA
## 17	0 NA NA NA
## 18	0 NA NA NA
## 19	0 NA NA NA
## 20	0 NA NA NA
## 21	0 NA NA NA
## 22	0 NA NA NA
## 23	0 NA NA NA
## 24	0 NA NA NA
## 25	0 NA NA NA
## 26	0 NA NA NA
## 27	0 NA NA NA
## 28	0 NA NA NA
## 29	0 NA NA NA
## 30	0 NA NA NA
## 31	0 NA NA NA
## 32	1 NA NA NA
## 33	0 NA NA NA
## 34	0 NA NA NA
## 35	0 NA NA NA
## 36	0 NA NA NA
## 37	0 NA NA NA
## 38	0 NA NA NA
## 39	0 NA NA NA
## 40	0 NA NA NA
## 41	0 NA NA NA
## 42	0 NA NA NA
## 43	0 NA NA NA
## 44	0 NA NA NA
## 45	0 NA NA NA
## 46	0 NA NA NA
## 47	0 NA NA NA
## 48	1 NA NA NA
## 49	0 NA NA NA
## 50	0 NA NA NA
## 51	0 NA NA NA
## 52	0 NA NA NA
## 53	0 NA NA NA
## 54	0 NA NA NA
## 55	0 NA NA NA
## 56	0 NA NA NA
## 57	0 NA NA NA
## 58	0 NA NA NA
## 59	0 NA NA NA
## 60	0 NA NA NA
## 61	0 NA NA NA
## 62	0 NA NA NA
## 63	0 NA NA NA
## 64	0 NA NA NA
## 65	0 NA NA NA
## 66	0 NA NA NA

```
## 67      0 NA  NA  NA
## 68      0 NA  NA  NA
## 69      0 NA  NA  NA
## 70      0 NA  NA  NA
## 71      0 NA  NA  NA
## 72      0 NA  NA  NA
## 73      0 NA  NA  NA
## 74      0 NA  NA  NA
## 75      0 NA  NA  NA
## 76      0 NA  NA  NA
## 77      0 NA  NA  NA
## 78      0 NA  NA  NA
## 79      0 NA  NA  NA
## 80      0 NA  NA  NA
## 81      0 NA  NA  NA
## 82      0 NA  NA  NA
## 83      0 NA  NA  NA
## 84      0 NA  NA  NA
## 85      0 NA  NA  NA
## 86      0 NA  NA  NA
## 87      0 NA  NA  NA
## 88      0 NA  NA  NA
## 89      0 NA  NA  NA
## 90      0 NA  NA  NA
## 91      0 NA  NA  NA
## 92      0 NA  NA  NA
## 93      0 NA  NA  NA
## 94      1 NA  NA  NA
## 95      0 NA  NA  NA
## 96      0 NA  NA  NA
## 97      0 NA  NA  NA
## 98      0 NA  NA  NA
## 99      0 NA  NA  NA
## 100     0 NA  NA  NA
## 101     0 NA  NA  NA
## 102     0 NA  NA  NA
## 103     0 NA  NA  NA
## 104     0 NA  NA  NA
## 105     0 NA  NA  NA
## 106     0 NA  NA  NA
## 107     0 NA  NA  NA
## 108     0 NA  NA  NA
## 109     0 NA  NA  NA
## 110     0 NA  NA  NA
## 111     0 NA  NA  NA
## 112     0 NA  NA  NA
## 113     0 NA  NA  NA
```

```
names(data_s)
```

```
##  [1] "RPI"          "W875RX1"      "DPCERA3M086SBEA" "INDPRO"
##  [5] "IPFPNSS"      "IPFINAL"      "IPCONGD"          "IPDCONGD"
##  [9] "IPNCONGD"     "IPBUSEQ"      "IPMAT"            "IPDMAT"
## [13] "IPNMAT"       "IPMANSICS"    "IPB51222s"        "IPFUELS"
## [17] "CUMFNS"       "HWI"          "HWIURATIO"        "CLF160V"
```

```
## [21] "CE160V"          "UNRATE"          "UEMPMEAN"        "UEMPLT5"
## [25] "UEMP5T014"       "UEMP150V"        "UEMP15T26"       "UEMP270V"
## [29] "CLAIMSx"         "PAYEMS"          "USGOOD"          "CES1021000001"
## [33] "USCONS"          "MANEMP"          "DMANEMP"         "NDMANEMP"
## [37] "SRVPRD"          "USTPU"           "USWTRADE"        "USTRADE"
## [41] "USFIRE"          "USGOVT"          "CES0600000007"   "AWOTMAN"
## [45] "AWHMAN"          "S.P.500"         "S.P..indust"     "S.P.div.yield"
## [49] "S.P.PE.ratio"    "WPSFD49207"      "WPSFD49502"      "WPSID61"
## [53] "WPSID62"         "OILPRICEx"       "PPICMM"          "CPIAUCSL"
## [57] "CPIAPPSL"        "CPITRNSL"        "CPIMEDSL"        "CUSR0000SAC"
## [61] "CUSR0000SAD"     "CUSR0000SAS"     "CPIULFSL"        "CUSR0000SAOL2"
## [65] "CUSR0000SAOL5"   "PCEPI"           "DDURRG3M086SBEA" "DNDGRG3M086SBEA"
## [69] "DSERRG3M086SBEA" "CES0600000008"   "CES2000000008"   "CES3000000008"
## [73] "CMRMTSPLx"       "RETAILx"         "HOUST"           "HOUSTW"
## [77] "PERMIT"          "PERMITNE"        "PERMITS"         "PERMITW"
## [81] "AMDMNOx"         "AMDMUOx"         "BUSINVx"         "ISRATIOx"
## [85] "M1SL"            "M2SL"            "M2REAL"          "TOTRESNS"
## [89] "NONBORRES"       "BUSLOANS"        "REALLN"          "NONREVSL"
## [93] "CONSPI"          "S.P.500.1"       "S.P..indust.1"   "S.P.div.yield.1"
## [97] "S.P.PE.ratio.1"  "CP3Mx"           "TB3MS"           "TB6MS"
## [101] "GS1"             "GS5"             "GS10"            "AAA"
## [105] "BAA"             "COMPAPFFx"       "TB3SMFFM"        "TB6SMFFM"
## [109] "T1YFFM"          "T5YFFM"          "T10YFFM"         "AAAFFM"
## [113] "BAAFFM"          "EXSZUSx"         "EXJPUSx"         "EXUSUKx"
## [117] "EXCAUSx"         "DTCOLNVHFNM"     "DTCTHFNM"        "INVEST"
## [121] "FEDFUNDS"
```

```
variables = c(grep("^FEDFUNDS$", colnames(data_s)), #Fed Funds Rate
  grep("^INDPRO$", colnames(data_s)), #IP Index
  grep("^CPIAUCSL$", colnames(data_s)), #CPI : All Items
  grep("^TB3MS$", colnames(data_s)), #3-Month Treasury Bill:
  grep("^GS5$", colnames(data_s)), #5-Year Treasury Rate
  grep("^M1SL$", colnames(data_s)), # M1 Money Stock
  grep("^M2SL$", colnames(data_s)), #M2 Money Stock
  grep("^EXJPUSx$", colnames(data_s)), #Japan / U.S. Foreign Exchange Rate
  grep("^CUSR0000SAC$", colnames(data_s)), #CPI : Commodities
  grep("^CUMFNS$", colnames(data_s)), #Capacity Utilization: Manufacturing
  grep("^DPCERA3M086SBEA$", colnames(data_s)), #Real personal consumption expenditures
  grep("^DDURRG3M086SBEA$", colnames(data_s)), #Personal Cons. Exp: Durable goods
  grep("^DNDGRG3M086SBEA$", colnames(data_s)), #Personal Cons. Exp: Nondurable goods
  grep("^UNRATE$", colnames(data_s)), #Civilian Unemployment Rate
  grep("^CE160V$", colnames(data_s)), #Civilian Employment
  grep("^CES0600000008$", colnames(data_s)), #Avg Hourly Earnings : Goods-Producing
  grep("^HOUST$", colnames(data_s)), #Housing Starts: Total New Privately Owned
  grep("^AMDMNOx$", colnames(data_s)), #New Orders for Durable Goods
  grep("^S.P.div.yield$", colnames(data_s)) #S&P s Composite Common Stock: Dividend Yield
)
length(variables)
```

```
## [1] 19
```

```
variable_names = c("Fed Funds Rate",
  "IP Index",
  "CPI",
  "3-Month Treasury Bill",
```

```

"5-Year Treasury Rate",
"M1 Money Stock",
"M2 Money Stock",
"Exchange rate: Japan/U.S.",
"CPI : Commodities",
"Capacity Utilization",
"Real personal consump.",
"Durable goods consump.",
"Nondurable goods consump.",
"Unemployment Rate",
"Employment",
"Avg Hourly Earnings",
"Housing Starts",
"New Orders",
"Dividend Yield")
length(variable_names)

## [1] 19

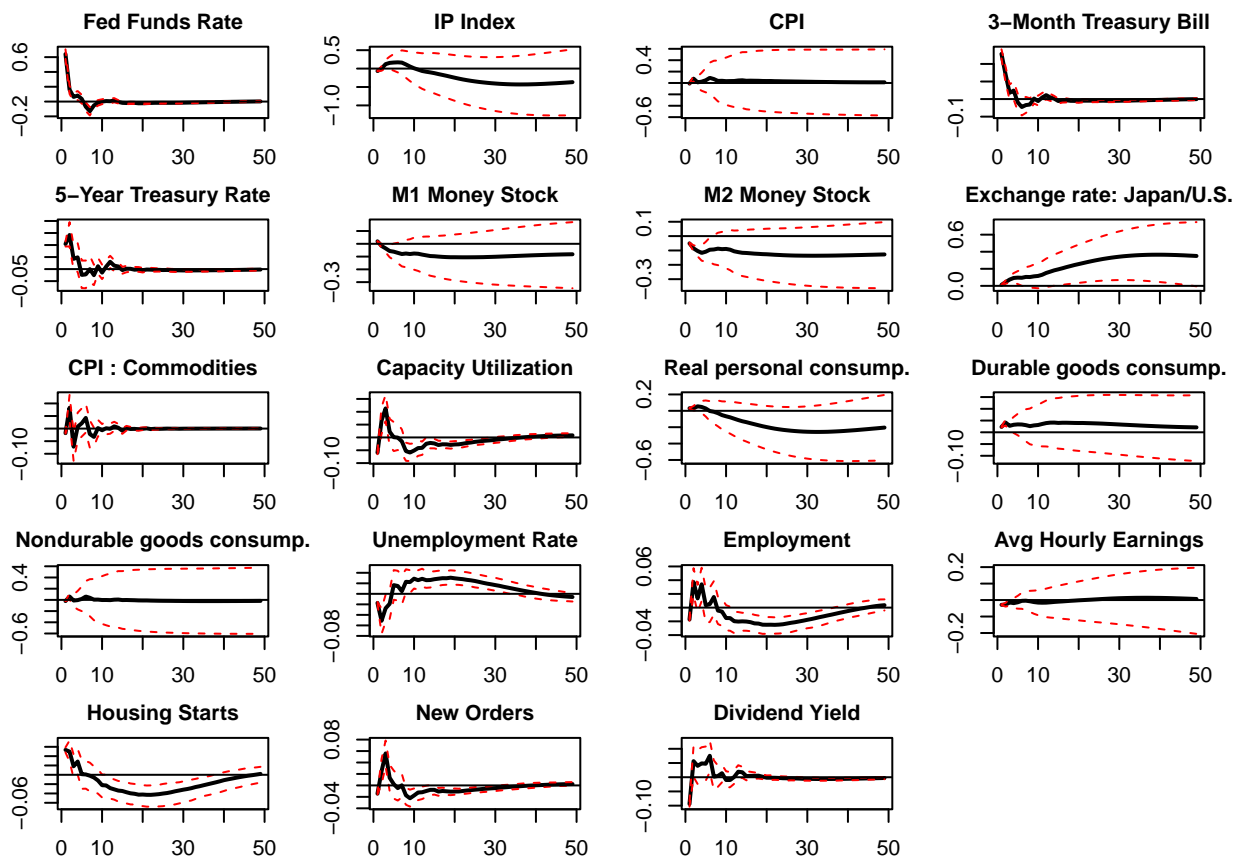
transf_code = c(1,5,5,1,1,5,5,5,1,1,5,5,5,1,1,5,1,1,1)
length(transf_code)

## [1] 19

options(repr.plot.width=12, repr.plot.height=8)

par(mfrow=c(5,4),
    mar = c(2, 2, 2, 2))
for(i in variables){
  index = which(variables == i)
  if(transf_code[index] == 5){
    plot(cumsum(IRF[,i]), type='l',lwd=2, main = variable_names[index],
         ylab= "", xlab="Steps", ylim=range(cumsum(Lower[,i]),cumsum(Upper[,i])),
         cex.main=1, cex.axis=1)
    lines(cumsum(Upper[,i]), lty=2, col="red")
    lines(cumsum(Lower[,i]), lty=2, col="red")
    abline(h=0)
  }
  else{
    plot(IRF[,i], type='l',lwd=2, main = variable_names[index],
         ylab= "", xlab="Steps", ylim=range((Lower[,i]),(Upper[,i])),
         cex.main=1, cex.axis=1)
    lines((Upper[,i]), lty=2, col="red")
    lines((Lower[,i]), lty=2, col="red")
    abline(h=0)
  }
}

```



Regresión de cada factor sobre cada serie

```
# Initialize an empty dataframe to store the results
results_df <- data.frame(Variable = character(0), Factor = character(0), R2 = numeric(0))

# Iterate through each factor in F_hat
for (factor_name in colnames(F_hat)) {
  # Extract the current factor
  current_factor <- F_hat[, factor_name]

  # Iterate through each column in data_s
  for (column_name in colnames(data_s)) {
    # Extract the current column
    current_column <- data_s[, column_name]

    # Perform linear regression
    regression_model <- lm(current_column ~ current_factor)

    # Calculate R-squared
    r_squared <- summary(regression_model)$r.squared

    # Add the results to the results dataframe
    results_df <- rbind(results_df, data.frame(Variable = column_name, Factor = factor_name, R2 = r_squared))
  }
}
```

```
results_df$R2 <- format(results_df$R2, scientific = FALSE)
results_df <- results_df[order(-as.numeric(results_df$R2)), ]
```

```
# Print the sorted results dataframe
print(head(results_df,20))
```

```
##      Variable Factor      R2
## 302   CUSR0000SAC   PC3 0.7851122457927
## 310 DNDGRG3M086SBEA PC3 0.7752439243947
## 14    IPMANSICS     PC1 0.7651868584029
## 306   CUSR0000SAOL2 PC3 0.7475006892248
## 4     INDPRO       PC1 0.7473794536251
## 298   CPIAUCSL     PC3 0.7353152585852
## 31    USGOOD       PC1 0.7308305028622
## 17    CUMFNS       PC1 0.7194671091465
## 307   CUSR0000SAOL5 PC3 0.6841655116794
## 34    MANEMP       PC1 0.6721827240774
## 170   S.P.PE.ratio PC2 0.6644681151674
## 218 S.P.PE.ratio.1 PC2 0.6644681151674
## 5     IPFPNSS      PC1 0.6630864490378
## 30    PAYEMS       PC1 0.6579379405403
## 169   S.P.div.yield PC2 0.6514120447114
## 217 S.P.div.yield.1 PC2 0.6514120447114
## 35    DMANEMP      PC1 0.6242410032609
## 308    PCEPI       PC3 0.6206402467961
## 167    S.P.500     PC2 0.5951692531138
## 215    S.P.500.1   PC2 0.5951692531138
```

```
average_r_squared_by_factor <- aggregate(R2 ~ Factor, data = results_df, FUN = function(x) mean(as.numeric(x)))
```

```
# Print the average R-squared values by factor
print(average_r_squared_by_factor)
```

```
##      Factor      R2
## 1      PC1 0.14423198
## 2      PC2 0.08318371
## 3      PC3 0.06376903
## 4      PC4 0.05110978
## 5      PC5 0.04248469
## 6      PC6 0.04180347
## 7      PC7 0.02956900
```

Step 5: FEVD

```
# Get the VAR point estimates
```

```
hor=60
```

```
irf_points = irf(var, n.ahead = hor, boot = FALSE)
```

```
# Get IRFs for all of X we are interested in, Dimensions: (hor, key_nvars)
```

```
# Find loadings
```

```
results = summary(reg_loadings) # the warning comes because of FEDFUNDS
```

```
key_nvars = length(variables)
```

```
key_nvars
```

```
## [1] 19
```



```

irf_X_pc1 = array(c(0,0), dim=c(hor+1, key_nvars))
irf_X_pc2 = array(c(0,0), dim=c(hor+1, key_nvars))
irf_X_pc3 = array(c(0,0), dim=c(hor+1, key_nvars))
irf_X_pc4 = array(c(0,0), dim=c(hor+1, key_nvars))
irf_X_pc5 = array(c(0,0), dim=c(hor+1, key_nvars))
irf_X_pc6 = array(c(0,0), dim=c(hor+1, key_nvars))
irf_X_pc7 = array(c(0,0), dim=c(hor+1, key_nvars))
irf_X_ffr = array(c(0,0), dim=c(hor+1, key_nvars))
for(i in 1:key_nvars){
  irf_X_pc1[,i] = irf_points$irf$PC1 %%% matrix(loadings[1:nrow(loadings), variables[i]])
  irf_X_pc2[,i] = irf_points$irf$PC2 %%% matrix(loadings[1:nrow(loadings), variables[i]])
  irf_X_pc3[,i] = irf_points$irf$PC3 %%% matrix(loadings[1:nrow(loadings), variables[i]])
  irf_X_pc4[,i] = irf_points$irf$PC3 %%% matrix(loadings[1:nrow(loadings), variables[i]])
  irf_X_pc5[,i] = irf_points$irf$PC3 %%% matrix(loadings[1:nrow(loadings), variables[i]])
  irf_X_pc6[,i] = irf_points$irf$PC3 %%% matrix(loadings[1:nrow(loadings), variables[i]])
  irf_X_pc7[,i] = irf_points$irf$PC3 %%% matrix(loadings[1:nrow(loadings), variables[i]])
  irf_X_ffr[,i] = (irf_points$irf$FEDFUNDS) %%% matrix(loadings[1:nrow(loadings), variables[i]])
}

```

Get the IRFs squared and accumulate them

```

psi2_pc1 = array(0, dim = key_nvars)
psi2_pc2 = array(0, dim = key_nvars)
psi2_pc3 = array(0, dim = key_nvars)
psi2_pc4 = array(0, dim = key_nvars)
psi2_pc5 = array(0, dim = key_nvars)
psi2_pc6 = array(0, dim = key_nvars)
psi2_pc7 = array(0, dim = key_nvars)
psi2_ffr = array(0, dim = key_nvars)

for(i in 1:key_nvars){
  for(j in 1:hor){
    psi2_pc1[i] = psi2_pc1[i] + irf_X_pc1[j,i]^2
    psi2_pc2[i] = psi2_pc2[i] + irf_X_pc2[j,i]^2
    psi2_pc3[i] = psi2_pc3[i] + irf_X_pc3[j,i]^2
    psi2_pc4[i] = psi2_pc4[i] + irf_X_pc4[j,i]^2
    psi2_pc5[i] = psi2_pc5[i] + irf_X_pc5[j,i]^2
    psi2_pc6[i] = psi2_pc6[i] + irf_X_pc6[j,i]^2
    psi2_pc7[i] = psi2_pc7[i] + irf_X_pc7[j,i]^2
    psi2_ffr[i] = psi2_ffr[i] + irf_X_ffr[j,i]^2
  }
}

```

```

var_total= array(0, dim = key_nvars)
var_fac= array(0, dim = key_nvars)
var_e= array(0, dim = key_nvars)

for(i in 1:key_nvars){
  var_fac[i] = psi2_pc1[i] + psi2_pc2[i] + psi2_pc3[i] + psi2_pc4[i]+psi2_pc5[i]+psi2_pc6[i]+psi2_pc7[i]
  var_total[i] = psi2_pc1[i] + psi2_pc2[i] + psi2_pc3[i] +psi2_pc4[i]+psi2_pc5[i]+psi2_pc6[i]+psi2_pc7[i]
  var_e[i] = results[[variables[i]]]$sigma^2
}

table = data.frame("PC1" = round((psi2_pc1),3),
                   "PC2" = round((psi2_pc2),3),

```

```

        "PC3" = round((psi2_pc3),3),
        "PC4" = round((psi2_pc4),3),
        "PC5" = round((psi2_pc5),3),
        "PC6" = round((psi2_pc6),3),
        "PC7" = round((psi2_pc7),3),
        "FEDFUNDS" = round((psi2_ffr),3),
        "Factor_Y_total" = round(var_fac,3) ,
        "e" = round((var_e),3),
        "Total" = round(var_total,3))
row.names(table) = variable_names
table

```

##	PC1	PC2	PC3	PC4	PC5	PC6	PC7	FEDFUNDS			
## Fed Funds Rate	0.076	0.125	0.014	0.014	0.014	0.014	0.014	0.565			
## IP Index	0.613	0.113	0.003	0.003	0.003	0.003	0.003	0.054			
## CPI	0.010	0.048	0.723	0.723	0.723	0.723	0.723	0.020			
## 3-Month Treasury Bill	0.087	0.093	0.010	0.010	0.010	0.010	0.010	0.114			
## 5-Year Treasury Rate	0.129	0.156	0.019	0.019	0.019	0.019	0.019	0.046			
## M1 Money Stock	0.024	0.023	0.001	0.001	0.001	0.001	0.001	0.003			
## M2 Money Stock	0.010	0.006	0.007	0.007	0.007	0.007	0.007	0.006			
## Exchange rate: Japan/U.S.	0.020	0.014	0.009	0.009	0.009	0.009	0.009	0.007			
## CPI : Commodities	0.007	0.047	0.773	0.773	0.773	0.773	0.773	0.020			
## Capacity Utilization	0.571	0.112	0.003	0.003	0.003	0.003	0.003	0.054			
## Real personal consump.	0.056	0.083	0.002	0.002	0.002	0.002	0.002	0.008			
## Durable goods consump.	0.001	0.003	0.024	0.024	0.024	0.024	0.024	0.001			
## Nondurable goods consump.	0.008	0.048	0.763	0.763	0.763	0.763	0.763	0.020			
## Unemployment Rate	0.148	0.078	0.001	0.001	0.001	0.001	0.001	0.028			
## Employment	0.096	0.066	0.001	0.001	0.001	0.001	0.001	0.019			
## Avg Hourly Earnings	0.009	0.001	0.001	0.001	0.001	0.001	0.001	0.001			
## Housing Starts	0.163	0.138	0.004	0.004	0.004	0.004	0.004	0.056			
## New Orders	0.100	0.031	0.003	0.003	0.003	0.003	0.003	0.009			
## Dividend Yield	0.047	0.733	0.027	0.027	0.027	0.027	0.027	0.029			
##	Factor_Y_total		e	Total							
## Fed Funds Rate		0.837	0.000	0.837							
## IP Index		0.796	0.080	0.876							
## CPI		3.692	0.243	3.935							
## 3-Month Treasury Bill		0.342	0.358	0.700							
## 5-Year Treasury Rate		0.428	0.164	0.591							
## M1 Money Stock		0.057	0.936	0.993							
## M2 Money Stock		0.057	0.938	0.995							
## Exchange rate: Japan/U.S.		0.087	0.882	0.968							
## CPI : Commodities		3.940	0.198	4.138							
## Capacity Utilization		0.752	0.100	0.852							
## Real personal consump.		0.159	0.837	0.995							
## Durable goods consump.		0.125	0.978	1.103							
## Nondurable goods consump.		3.892	0.206	4.099							
## Unemployment Rate		0.260	0.632	0.892							
## Employment		0.185	0.696	0.881							
## Avg Hourly Earnings		0.018	0.972	0.990							
## Housing Starts		0.375	0.141	0.516							
## New Orders		0.156	0.845	1.001							
## Dividend Yield		0.943	0.091	1.034							

```

r2 = array(0, dim = key_nvars)
for(i in 1:key_nvars){
  r2[i] = results[[variables[i]]]$r.squared
}

table2 = data.frame("Variables" = variable_names, "Contribution" = round((psi2_ffr/var_total),3), "R-squared" = r2)
table2

```

##	Variables	Contribution	R.squared
## 1	Fed Funds Rate	0.675	1.000
## 2	IP Index	0.061	0.921
## 3	CPI	0.005	0.760
## 4	3-Month Treasury Bill	0.163	0.646
## 5	5-Year Treasury Rate	0.078	0.838
## 6	M1 Money Stock	0.003	0.075
## 7	M2 Money Stock	0.006	0.073
## 8	Exchange rate: Japan/U.S.	0.007	0.129
## 9	CPI : Commodities	0.005	0.805
## 10	Capacity Utilization	0.063	0.901
## 11	Real personal consump.	0.008	0.173
## 12	Durable goods consump.	0.001	0.034
## 13	Nondurable goods consump.	0.005	0.796
## 14	Unemployment Rate	0.032	0.376
## 15	Employment	0.022	0.313
## 16	Avg Hourly Earnings	0.002	0.040
## 17	Housing Starts	0.108	0.861
## 18	New Orders	0.009	0.165
## 19	Dividend Yield	0.029	0.910

Predicciones de los factores y FFR

Model Performance

```

# Convert the date_column to Date type
df_test$index <- as.Date(df_test$index)
test_set=df_test[,2:ncol(df_test)]
actual_df=scale(test_set, center = TRUE, scale = TRUE)
# Create an xts object with the date_column as the index
xts_test <- xts(df_test[, -which(colnames(df_test) == "index")], order.by = df_test$index)
cat("Rango de datos:", as.character(range(index(xts_test))), "\n")

```

```
## Rango de datos: 2008-02-01 2020-02-01
```

```

data_test_s = scale(xts_test, center = TRUE, scale = TRUE)
cat("Tamaño de mi muestra de prueba:", dim(df_test), "\n")

```

```
## Tamaño de mi muestra de prueba: 145 122
```

```

predicciones=predict(var, n.ahead = dim(df_test)[1])
pred_F=predicciones[,1:7]
pred_FFR=predicciones[,ncol(predicciones)]
dim(pred_F)

```

```
## [1] 145 7
```

```

length(pred_FFR)

## [1] 145
F_part=pred_F%*%Lamda_F
dim(F_part)

## [1] 145 121
Y_part=outer(pred_FFR, Lambda_ffr)
dim(Y_part)

## [1] 145 121
X_pred=F_part+Y_part
X_forec=as.data.frame(X_pred)
dim(X_pred)

## [1] 145 121
X_predictions <- as.data.frame(X_pred)
dim(X_predictions)

## [1] 145 121
predictions_df <- as.data.frame(X_pred)
dim(predictions_df)

## [1] 145 121
dim(actual_df)

## [1] 145 121
sum(is.na(actual_df))

## [1] 0
sum(is.na(predictions_df))

## [1] 0
compute_accuracy_measures_df <- function(actual_df, predictions_df) {
  if(ncol(actual_df) != ncol(predictions_df) || nrow(actual_df) != nrow(predictions_df)) {
    stop("Dimensions of actual and predicted data must match.")
  }

  measures_list <- list()

  for(i in 1:ncol(actual_df)) {
    actual <- actual_df[, i]
    predicted <- predictions_df[, i]

    # MAE
    mae <- mean(abs(actual - predicted), na.rm = TRUE)

    # MSE
    mse <- mean((actual - predicted)^2, na.rm = TRUE)

    # MAPE

```

```

mape <- mean(abs((actual - predicted) / actual) * 100, na.rm = TRUE)

# RMSFE (Root Mean Squared Forecast Error)
rmsfe <- sqrt(mse)

# Store in list
measures_list[[colnames(actual_df)[i]]] <- c(MAE = mae, MSE = mse, MAPE = mape, RMSFE = rmsfe)
}

# Convert the list to a dataframe
results_df <- do.call(rbind, measures_list)
return(results_df)
}

# Usage:
results_df <- compute_accuracy_measures_df(actual_df, predictions_df)

# View the results:
print(results_df)

```

##	MAE	MSE	MAPE	RMSFE
## RPI	0.5618468	1.0004828	98.02350	1.0002414
## W875RX1	0.6642520	0.9609458	156.97945	0.9802784
## DPCERA3M086SBEA	0.7283913	0.9896897	104.38534	0.9948315
## INDPRO	0.6535803	0.9356030	96.56096	0.9672658
## IPFPNSS	0.7134571	0.9498812	513.33549	0.9746185
## IPFINAL	0.7371293	0.9702203	111.11108	0.9849976
## IPCONGD	0.7508497	1.0007265	108.16845	1.0003632
## IPDCONGD	0.7034448	0.9952014	105.67586	0.9975978
## IPNCONGD	0.7755643	0.9986313	118.28217	0.9993154
## IPBUSEQ	0.6580432	0.9182772	180.82942	0.9582678
## IPMAT	0.6185695	0.9438401	155.28916	0.9715143
## IPDMAT	0.6355494	0.9263535	108.66071	0.9624726
## IPNMAT	0.5846706	0.9500400	112.73065	0.9747000
## IPMANSICS	0.6206304	0.9121185	108.53528	0.9550489
## IPB51222s	0.7490610	0.9954915	102.12360	0.9977432
## IPFUELS	0.5945564	0.9922318	110.17600	0.9961083
## CUMFNS	0.6397009	0.9081204	106.68085	0.9529535
## HWI	0.7769355	0.9676485	109.18395	0.9836913
## HWIURATIO	0.7448308	0.9540082	121.16400	0.9767335
## CLF160V	0.7958246	0.9966642	101.94263	0.9983307
## CE160V	0.6975852	0.9159273	152.09592	0.9570409
## UNRATE	0.7389095	0.9276468	121.24935	0.9631442
## UEMPMEAN	0.7906770	0.9944448	102.98289	0.9972185
## UEMPLT5	0.7794981	0.9911097	100.23660	0.9955449
## UEMP5T014	0.7505417	0.9767271	104.35726	0.9882950
## UEMP150V	0.7243066	0.8898898	114.16768	0.9433397
## UEMP15T26	0.8063647	0.9584598	110.94469	0.9790096
## UEMP270V	0.7172427	0.9134470	119.08047	0.9557442
## CLAIMSx	0.7107376	0.9657381	122.45505	0.9827198
## PAYEMS	0.6398495	0.8229099	107.60152	0.9071438
## USGOOD	0.6103140	0.8503756	119.78109	0.9221581
## CES1021000001	0.7862107	0.9670563	108.14013	0.9833902
## USCONS	0.6961875	0.9017496	108.66138	0.9496050

## MANEMP	0.5737396	0.8672230	112.10506	0.9312481
## DMANEMP	0.5698727	0.8667288	206.25692	0.9309827
## NDMANEMP	0.6586263	0.9247397	103.52224	0.9616339
## SRVPRD	0.6603295	0.8384021	133.44142	0.9156430
## USTPU	0.6385707	0.7818389	103.20207	0.8842165
## USWTRADE	0.6133453	0.7507438	111.49063	0.8664547
## USTRADEx	0.7076643	0.8468747	109.09245	0.9202580
## USFIRE	0.6827171	0.8545981	102.36951	0.9244447
## USGOVT	0.5349203	1.0009624	487.43427	1.0004811
## CES0600000007	0.7328069	0.9549635	116.81466	0.9772223
## AWOTMAN	0.6843572	0.9830384	187.86572	0.9914830
## AWHMAN	0.7151563	0.9466323	160.88471	0.9729503
## S.P.500	0.6789562	1.0124350	97.19548	1.0061983
## S.P..indust	0.6921639	1.0076597	102.88473	1.0038225
## S.P.div.yield	0.6106931	1.0033801	139.08940	1.0016886
## S.P.PE.ratio	0.5807283	0.9533385	150.12285	0.9763906
## WPSFD49207	0.7459585	1.0018488	100.35930	1.0009240
## WPSFD49502	0.7433832	1.0026810	100.38459	1.0013396
## WPSID61	0.6874479	1.0072619	102.97461	1.0036244
## WPSID62	0.7534529	0.9963598	103.48901	0.9981782
## OILPRICEx	0.7707803	0.9962265	100.81154	0.9981115
## PPICMM	0.7719529	0.9969898	100.46279	0.9984938
## CPIAUCSL	0.6900578	1.0050928	104.37015	1.0025432
## CPIAPPSL	0.7701128	0.9915085	102.54656	0.9957452
## CPITRNSL	0.7031779	0.9998761	107.35668	0.9999381
## CPIMEDSL	0.7589266	0.9912921	101.27987	0.9956365
## CUSR0000SAC	0.7056888	1.0001457	113.64539	1.0000729
## CUSR0000SAD	0.6717970	0.9956913	99.53376	0.9978433
## CUSR0000SAS	0.7394475	0.9993883	100.32255	0.9996941
## CPIULFSL	0.6904599	1.0053194	100.60104	1.0026562
## CUSR0000SA0L2	0.6893045	1.0022537	109.56869	1.0011262
## CUSR0000SA0L5	0.6894633	1.0042186	112.34347	1.0021071
## PCEPI	0.7431406	1.0022619	101.50509	1.0011303
## DDURRG3M086SBEA	0.7739557	0.9951336	99.66004	0.9975638
## DNDGRG3M086SBEA	0.7085461	0.9982366	111.53742	0.9991179
## DSERRG3M086SBEA	0.7533352	0.9940354	103.10846	0.9970132
## CES0600000008	0.7566106	0.9933512	159.59242	0.9966701
## CES2000000008	0.6544714	0.9937314	220.84134	0.9968608
## CES3000000008	0.8115256	0.9928263	123.21243	0.9964067
## CMRMTSPLx	0.6986956	0.9361116	103.86839	0.9675286
## RETAILx	0.6690447	0.9660654	114.02829	0.9828863
## HOUST	0.9344915	1.1241834	148.74650	1.0602752
## HOUSTW	0.8882142	1.0848530	133.59885	1.0415628
## PERMIT	0.9198235	1.0914745	141.43140	1.0447366
## PERMITNE	0.8428695	1.1135936	116.19665	1.0552694
## PERMITS	0.8776308	1.0182284	154.03583	1.0090730
## PERMITW	0.8950875	1.0591890	261.37391	1.0291691
## AMDMNOx	0.6858900	0.9813545	122.16197	0.9906334
## AMDMUOx	0.6872679	0.9256854	140.37693	0.9621255
## BUSINVx	0.6478314	0.8174486	347.59419	0.9041287
## ISRATIOx	0.6762397	0.9826996	104.71562	0.9913120
## M1SL	0.7347551	0.9918470	101.06356	0.9959151
## M2SL	0.6767094	0.9928024	101.61691	0.9963947
## M2REAL	0.6711623	1.0182486	108.38954	1.0090831

```

## TOTRESNS      0.5807679 0.9936251 107.87569 0.9968075
## NONBORRES     0.6242403 0.9918978 107.08913 0.9959407
## BUSLOANS      0.6855052 0.9912161 99.82063 0.9955983
## REALLN        0.5656532 0.9934957 102.21174 0.9967426
## NONREVSL      0.4258184 0.9939795 123.38903 0.9969852
## CONSPI        0.5042471 1.0083480 143.84085 1.0041653
## S.P.500.1     0.6789562 1.0124350 97.19548 1.0061983
## S.P..indust.1 0.6921639 1.0076597 102.88473 1.0038225
## S.P.div.yield.1 0.6106931 1.0033801 139.08940 1.0016886
## S.P.PE.ratio.1 0.5807283 0.9533385 150.12285 0.9763906
## CP3Mx         0.4095981 0.9050329 119.38964 0.9513322
## TB3MS         0.4713963 0.8627254 124.84243 0.9288301
## TB6MS         0.5061056 0.8694881 156.16957 0.9324635
## GS1           0.5425923 0.8928955 123.78797 0.9449315
## GS5           0.7528440 0.9827239 102.59340 0.9913243
## GS10          0.7192136 0.9952342 107.66105 0.9976143
## AAA           0.6953148 1.0061838 135.85786 1.0030871
## BAA           0.6341287 0.9934204 396.57686 0.9967048
## COMPAPFFx     0.5859761 0.8852618 157.46378 0.9408835
## TB3SMFFM      0.4734592 0.9459452 137.38396 0.9725971
## TB6SMFFM      0.5156534 0.8888303 187.02056 0.9427780
## T1YFFM        0.5946082 0.8532528 117.31816 0.9237169
## T5YFFM        0.6861606 0.7644588 107.61625 0.8743334
## T10YFFM       0.6951674 0.7998536 192.78772 0.8943453
## AAAFFM        0.7162795 0.8186033 115.60422 0.9047670
## BAAFFM        0.6742173 0.7851883 142.90880 0.8861085
## EXSZUSx       0.7263824 0.9740320 99.51583 0.9869306
## EXJPUSx       0.7553119 0.9853552 101.61120 0.9926506
## EXUSUKx       0.7289075 0.9702972 178.97749 0.9850366
## EXCAUSx       0.7346908 0.9876587 99.87368 0.9938102
## DTCOLNVHFNM   0.4364153 0.9928699 114.73541 0.9964286
## DTCTHFNM      0.6760860 0.9911279 99.77615 0.9955541
## INVEST        0.5917606 0.9915638 101.25435 0.9957729
## FEDFUNDS      0.4325386 0.7971550 126.17372 0.8928354

```

```

averages <- colMeans(results_df, na.rm = TRUE)
# Print the averages:
print(averages)

```

```

##          MAE          MSE          MAPE          RMSFE
## 0.6816715 0.9577956 131.7726453 0.9780051

```