Lista 3 de Econometria

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November 2023

Importando dados

Inicialmente, vamos importar os dados gerados no Excel.

```
dados_var_bruto <- read_xls(
  path = "./dados_lista3.xls",
  sheet = "Dados VAR"
  ) %>%
  mutate(
    date = as_date(date)
  )
```

```
dados_gmm <- read_xls(
  path = "./dados_lista3.xls",
  sheet = "Dados GMM"
  ) %>%
  mutate(
    date = as_date(date)
  )
```

Modelo VAR

Tirar log diferenças

```
dados_var <- dados_var_bruto %>%
  mutate(
    log_dif_c = log(c/lag(c)),
    log_dif_R = log_R-lag(log_R)
    ) %>%
  filter(
    date > "1970-10-01"
  )
```

Teste de Raíz Unitária

Teste de Philips-Perron

Primeiro, para a série Log Diferença dos Retornos do T-Bill.

```
pp.test(dados_var$log_dif_R) %>%
  tidy() %>%
  kable(
    col.names = c(
```

```r
      "Statistic: Dickey-Fuller Z (alpha)",
      "P Value",
      "Parameter: Truncation lag",
      "Method",
      "Alternative Hypothesis"
      ),
    caption = "Teste Philips Perron: Série Log Dif Retornos"
    )
```

Table 1: Teste Philips Perron: Série Log Dif Retornos

Statistic: Dickey-Fuller Z (alpha)	P Value	Parameter: Truncation lag	Method	Alternative Hypothesis
-187.2845	0.01	4	Phillips-Perron Unit Root Test	stationary

Agora, para a Log-Diferença do Consumo.

```r
pp.test(dados_var$log_dif_c) %>%
  tidy() %>%
  kable(
    col.names = c(
      "Statistic: Dickey-Fuller Z (alpha)",
      "P Value",
      "Parameter: Truncation lag",
      "Method",
      "Alternative Hypothesis"
      ),
    caption = "Teste Philips Perron: Série Log Dif do Consumo"
    )
```

Table 2: Teste Philips Perron: Série Log Dif do Consumo

Statistic: Dickey-Fuller Z (alpha)	P Value	Parameter: Truncation lag	Method	Alternative Hypothesis
-237.6015	0.01	4	Phillips-Perron Unit Root Test	stationary

Augmented Dickey-Fuller

```r
adf.test(dados_var$log_dif_R) %>%
  tidy() %>%
  kable(
    col.names = c(
      "Statistic: Dickey-Fuller Z (alpha)",
      "P Value",
      "Parameter: Truncation lag",
      "Method",
      "Alternative Hypothesis"
      ),
    caption = "Teste Augmented Dickey-Fuller: Série Log Dif do Retorno"
    )
```

Table 3: Teste Augmented Dickey-Fuller: Série Log Dif do Retorno

Statistic: Dickey-Fuller Z (alpha)	P Value	Parameter: Truncation lag	Method	Alternative Hypothesis
-5.119319	0.01	5	Augmented Dickey-Fuller Test	stationary

```r
adf.test(dados_var$log_dif_c) %>%
  tidy() %>%
  kable(
    col.names = c(
      "Statistic: Dickey-Fuller Z (alpha)",
      "P Value",
      "Parameter: Truncation lag",
      "Method",
      "Alternative Hypothesis"
      ),
    caption = "Teste Augmented Dickey-Fuller: Série Log Dif do Consumo"
    )
```

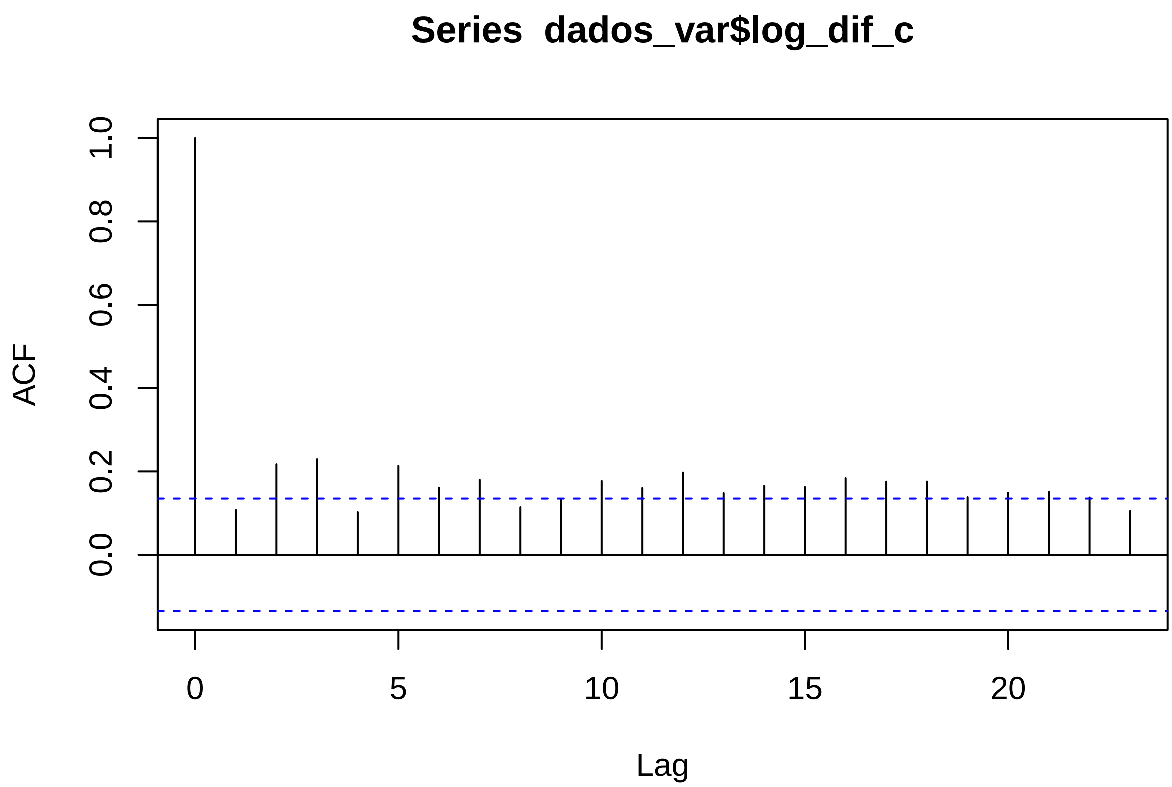
Table 4: Teste Augmented Dickey-Fuller: Série Log Dif do Consumo

Statistic: Dickey-Fuller Z (alpha)	P Value	Parameter: Truncation lag	Method	Alternative Hypothesis
-4.915244	0.01	5	Augmented Dickey-Fuller Test	stationary

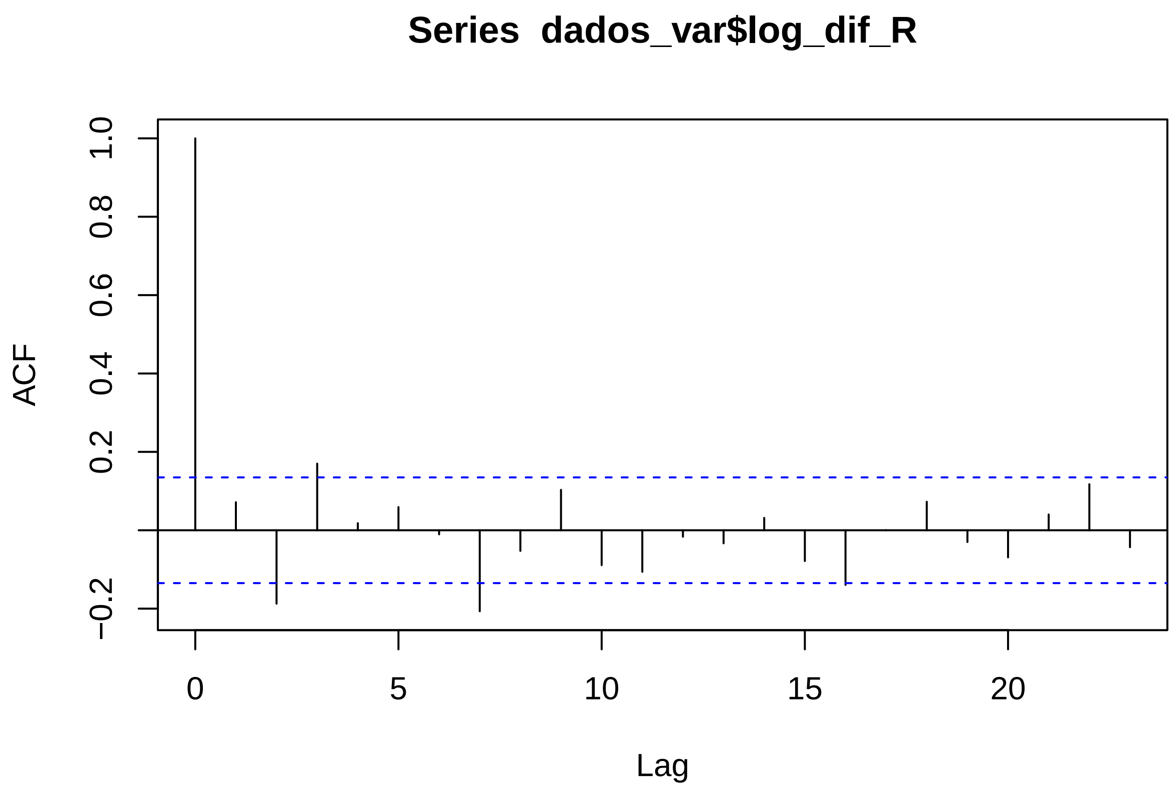
Funções de Autocorrelação

FAC

```r
acf(dados_var$log_dif_c)
```

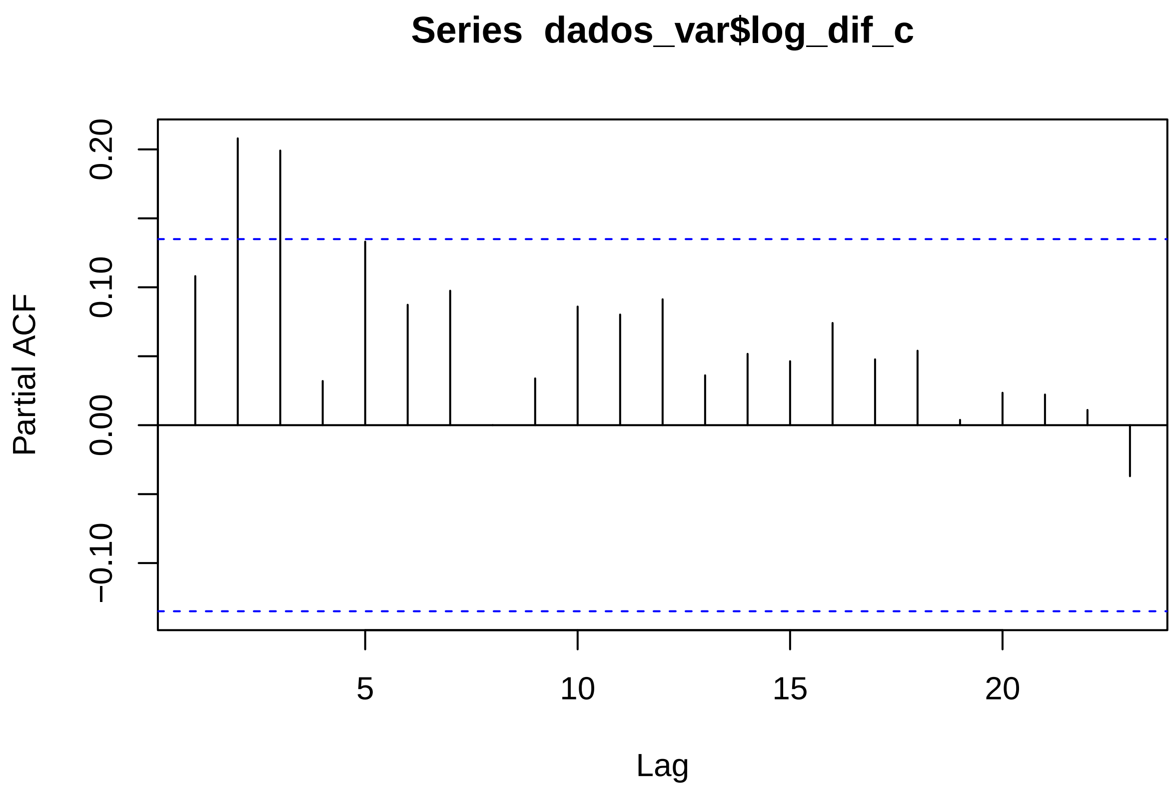



```
acf(dados_var$log_dif_R)
```

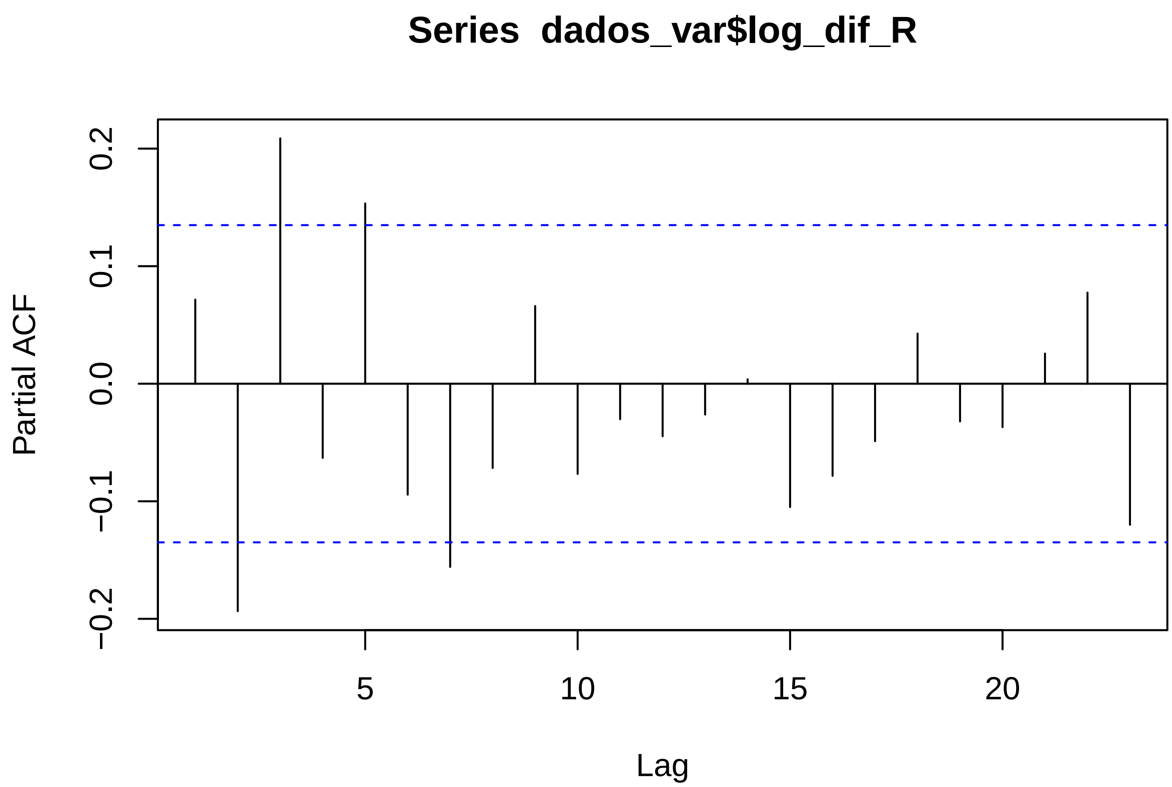


FACP

```
pacf(dados_var$log_dif_c)
```




```r
pacf(dados_var$log_dif_R)
```



Critérios de Informação

Utilizamos a função VARselect que retorna a ordem que minimiza os critérios de informação.

```
VARselect(
  y = dados_var[,4:5],
  lag.max = 5,
  type = "const"
)$selection %>%
  tidy() %>%
  kable(
    col.names = c(
      "Criteria",
      "Order"
    )
  )
```

Criteria	Order
AIC(n)	3
HQ(n)	3
SC(n)	1
FPE(n)	3

Os critérios AIC e HQ sugerem ordem 3, mas o critério BIC (SC) sugere ordem 1. Pelas FAC e FACP acreditamos que a ordem 3 faça mais sentido nesse caso. Faremos os dois casos.

Modelagem VAR

```
var1 <- VAR(
  y = dados_var[,4:5],
  p = 1,
  type = "const"
)
```

```
var3 <- VAR(
  y = dados_var[,4:5],
  p = 3,
  type = "const"
)
```

```
m1 <- var1$varresult
m3 <- var3$varresult
```

Var (1)

```
stargazer(
  m1,
  header = FALSE
  )
```

Table 6:

	Dependent variable:	
	y	
	(1)	(2)
log_dif_c.l1	0.109	0.078***
	(0.069)	(0.020)
log_dif_R.l1	0.089	0.077
	(0.229)	(0.067)
const	0.014***	−0.001***
	(0.001)	(0.0004)
Observations	210	210
R^2	0.012	0.073
Adjusted R^2	0.003	0.064
Residual Std. Error (df = 207)	0.013	0.004
F Statistic (df = 2; 207)	1.306	8.126***
Note:	*p<0.1; **p<0.05; ***p<0.01	

Var (3)

```
stargazer(
  m3,
  header = FALSE
  )
```

Table 7:

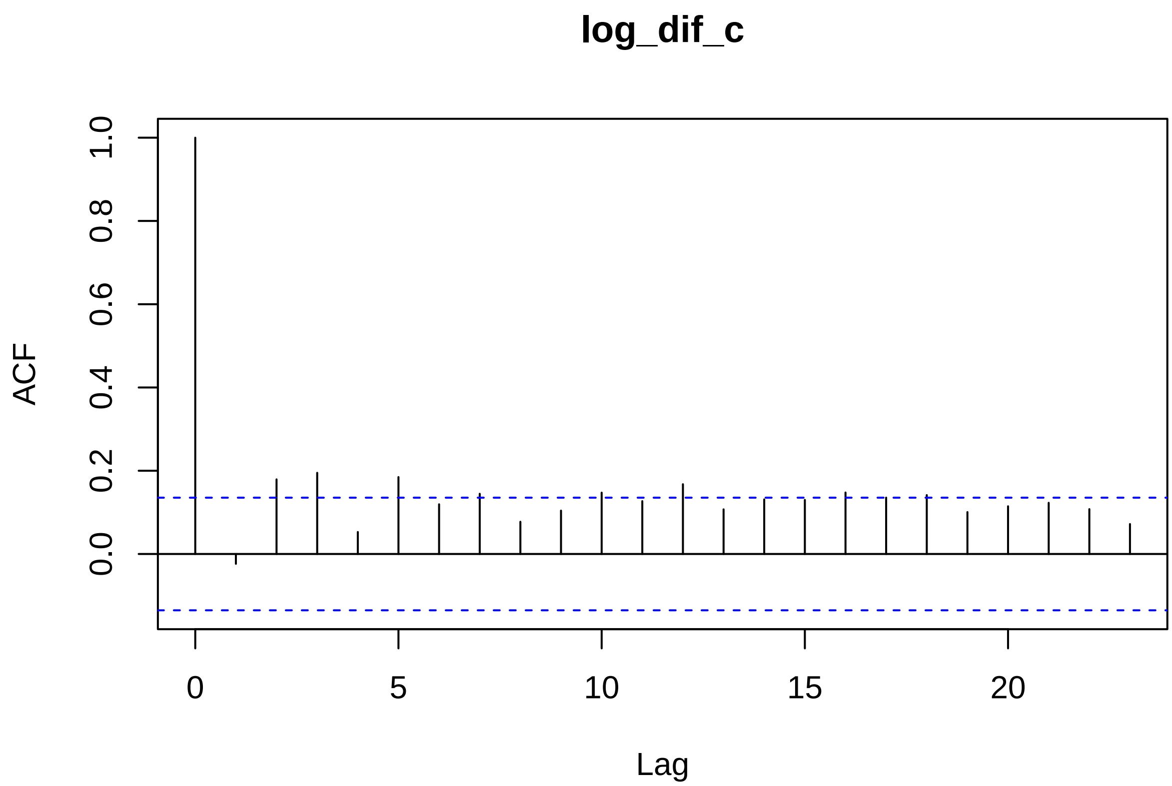
	Dependent variable:	
	y	
	(1)	(2)
log_dif_c.l1	0.040	0.074^{***}
	(0.069)	(0.020)
log_dif_R.l1	−0.130	0.135^{*}
	(0.237)	(0.069)
log_dif_c.l2	0.201^{***}	−0.006
	(0.071)	(0.020)
log_dif_R.l2	−0.106	-0.235^{***}
	(0.233)	(0.068)
log_dif_c.l3	0.209^{***}	0.022
	(0.071)	(0.021)
log_dif_R.l3	−0.065	0.211^{***}
	(0.229)	(0.066)
const	0.009^{***}	-0.001^{***}
	(0.002)	(0.001)
Observations	208	208
R^2	0.095	0.157
Adjusted R^2	0.068	0.132
Residual Std. Error (df = 201)	0.012	0.004
F Statistic (df = 6; 201)	3.516^{***}	6.240^{***}
Note:	*p<0.1; **p<0.05; ***p<0.01	

Análise de Resíduos

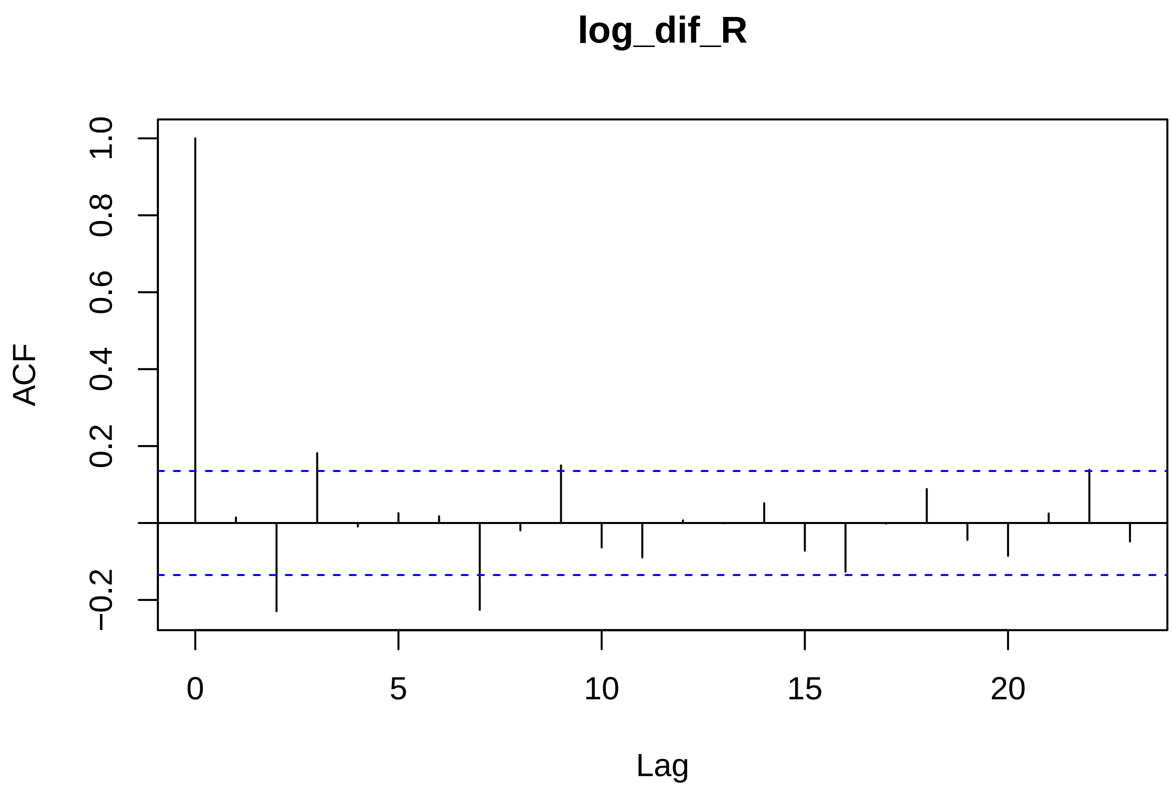
VAR (1)

```
r1 <- residuals(var1) %>% as_tibble()
```

```
acf(r1[,1])
```



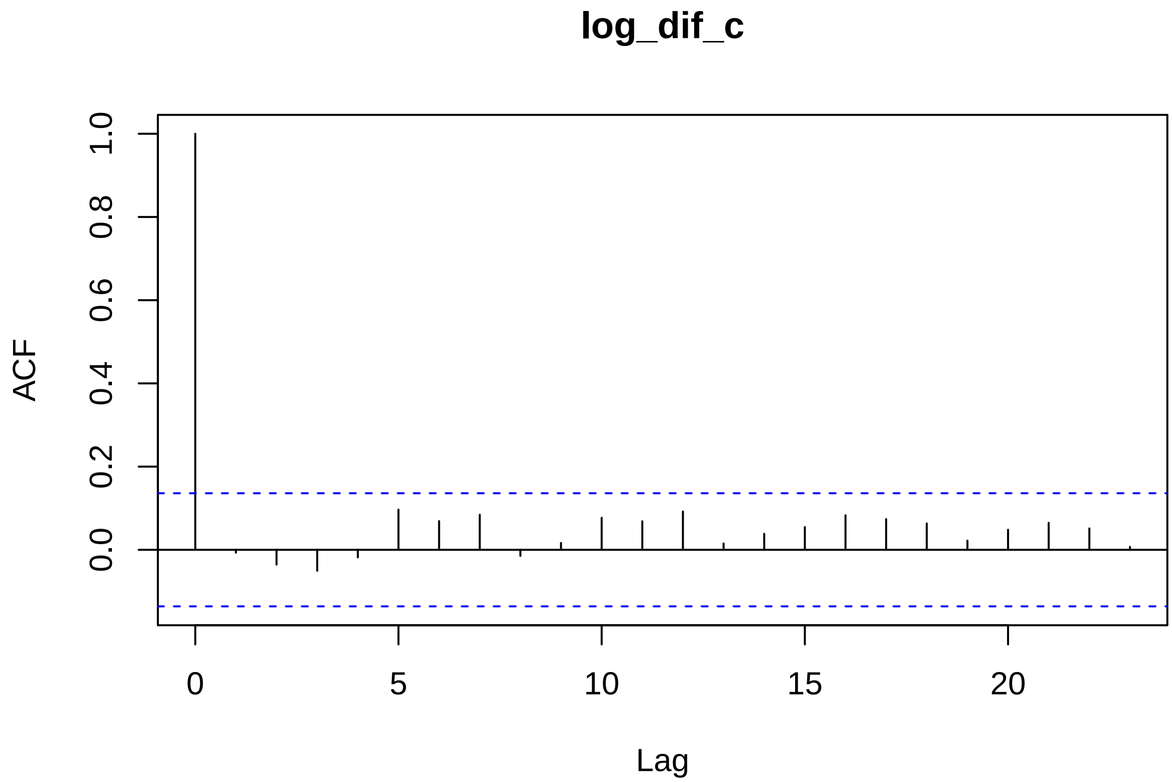

```
acf(r1[,2])
```



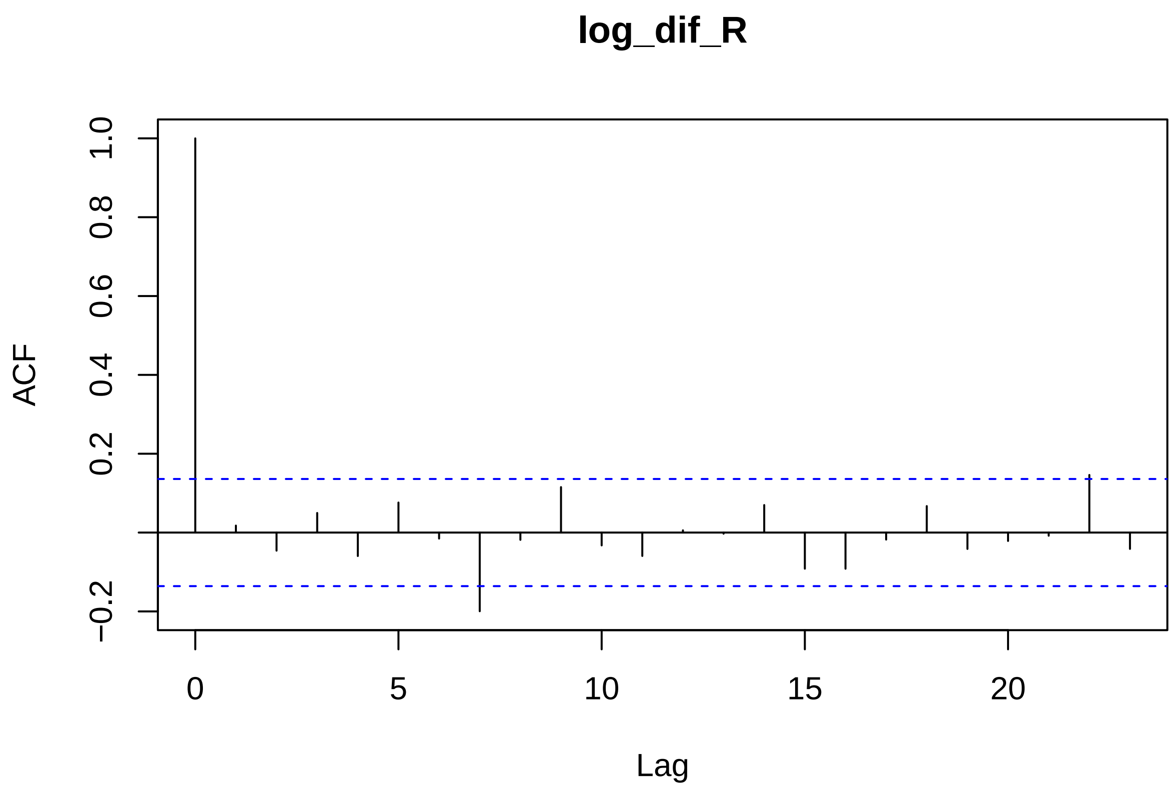
VAR (3)

```r
r3 <- residuals(var3) %>% as_tibble()
```

```r
acf(r3[,1])
```




```
acf(r3[,2])
```



Matriz de resposta aos choques

```
s3 <- summary(var3)
```

```
stargazer(
  s3$covres,
  header = FALSE,
  digits = 10
  )
```

Table 8:

	log_dif_c	log_dif_R
log_dif_c	0.0001555674	-0.0000028258
log_dif_R	-0.0000028258	0.0000130495

Função de Resposta a Impulso

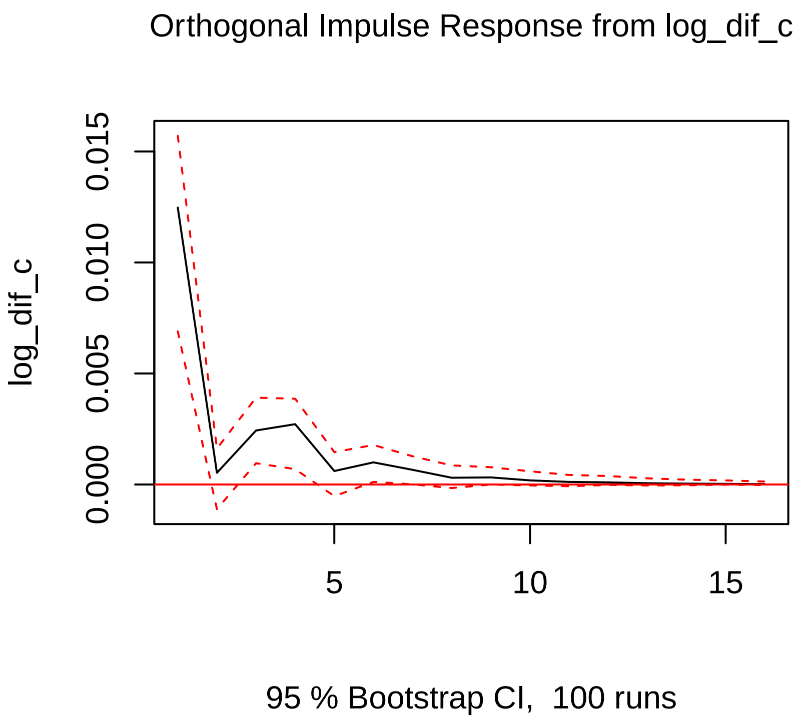
Geração das funções

```
irf3_cc <- irf(
  var3,
  impulse = "log_dif_c",
  response = "log_dif_c",
```

```
  n.ahead = 15
  )

irf3_cR <- irf(
  var3,
  impulse = "log_dif_c",
  response = "log_dif_R",
  n.ahead = 15
  )

irf3_RR <- irf(
  var3,
  impulse = "log_dif_R",
  response = "log_dif_R",
  n.ahead = 15
  )

irf3_Rc <- irf(
  var3,
  impulse = "log_dif_R",
  response = "log_dif_c",
  n.ahead = 15
  )
```

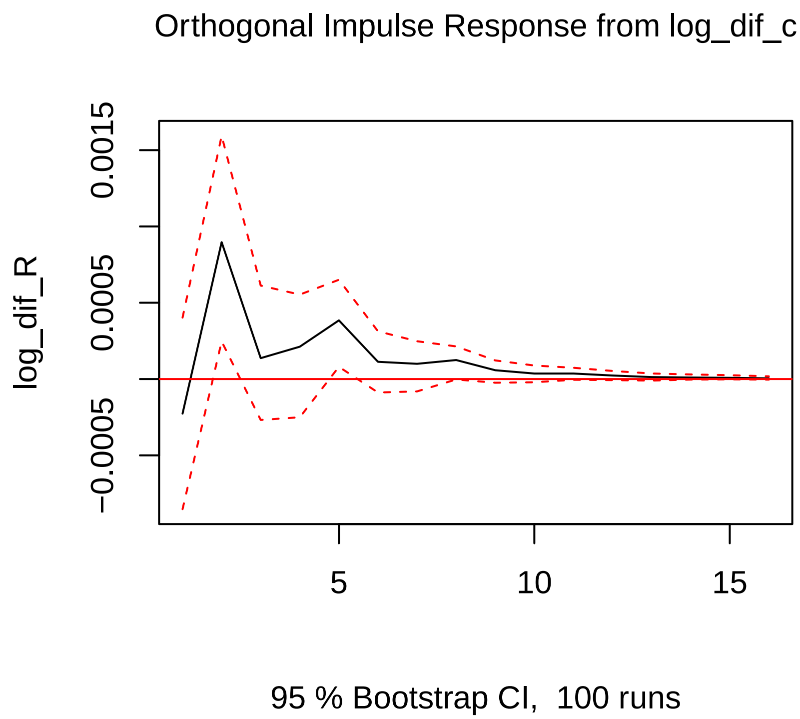
Impulso do Consumo no Consumo

```
plot(irf3_cc)
```



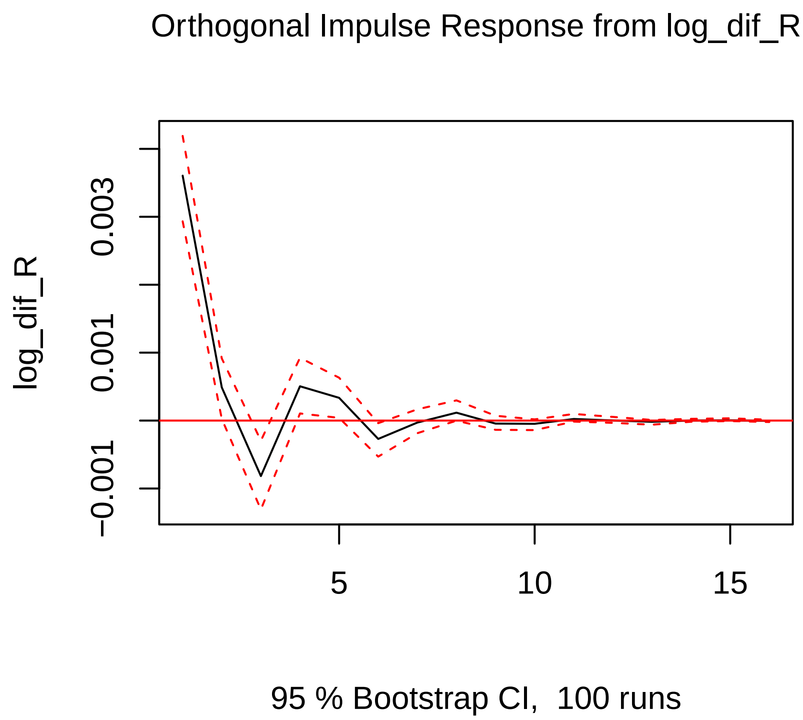
Impulso do Consumo no Retorno

```
plot(irf3_cR)
```



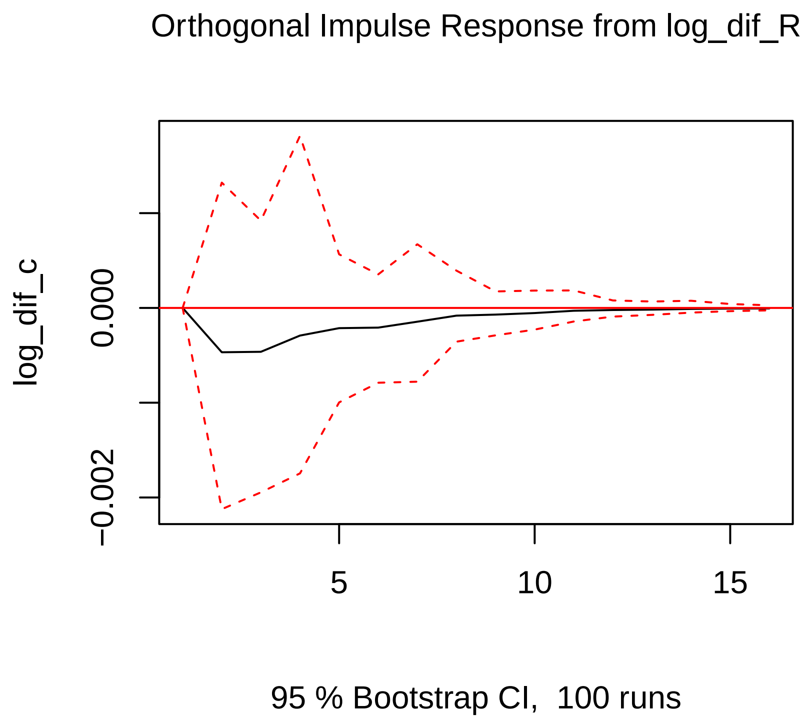
Impulso do Retorno no Retorno

```
plot(irf3_RR)
```



Impulso do Retorno no Consumo

```
plot(irf3_Rc)
```



Coeficiente de Aversão Absoluta ao Risco

Covariância(C,R)/Covariancia(R,R)

Qual matriz de cov usar? A das variáveis ou dos resíduos da regressão?

```
cov(dados_var[,4:5])
```

```
##              log_dif_c     log_dif_R
## log_dif_c  1.654027e-04 -1.128195e-06
## log_dif_R -1.128195e-06  1.496503e-05
```

```
print("")
```

```
## [1] ""
```

```
s3$covres
```

```
##              log_dif_c     log_dif_R
## log_dif_c  1.555674e-04 -2.825764e-06
## log_dif_R -2.825764e-06  1.304946e-05
```

CARA se for pela matriz das variáveis:

```
cov(dados_var[,4:5])[1,2]/cov(dados_var[,4:5])[2,2]
```

```
## [1] -0.07538876
```

CARA se for pela matriz sigma:

```
s3$covres[1,2]/s3$covres[2,2]
```

```
## [1] -0.2165426
```