Sesión 11: Corrección Tarea de Análisis de Factores

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Índice

1. Introducción

Se tienen datos con los tipos de cambio reales (respecto a USD) de varias economias (periodo 1970-2010). El objetivo es implementar el procedimiento inferencial de análisis de factores para estos datos utilizando uno y dos factores para comparar si el primer factor en ambos casos es similar o no.

2. Datos

```r
# Se cargan los paquetes
library("fields")
library("mnormt")
library("MCMCpack")
library("actuar")
library("ggplot2")
library("kernlab")
library("tidyverse")
library("readr")
library("psych")
```

```r
library("mvtnorm")
library("MASS")
library("xlsx")
library("knitr")
```

```r
# Función para extraer modas
getmode <- function(v) {
   uniqv <- unique(v)
   uniqv[which.max(tabulate(match(v, uniqv)))]
}
```

Leemos los datos correspondientes a los tipos de cambio de distintas economías. Se tienen 492 observaciones mensuales para 80 economías.

```r
# Cargamos los datos)
data<-read.xlsx("../01_Notas_Ovando/est46114_s06_data.xls",sheetName = 'RealXR_Data')

# Obtenemos las dimensiones de los datos
dim(data)
```

```
## [1] 492  81
```

```r
# Extraemos las fechas
fechas<-data$Date

data<-select(data,-Date)
```

2.1. Análisis exploratorio

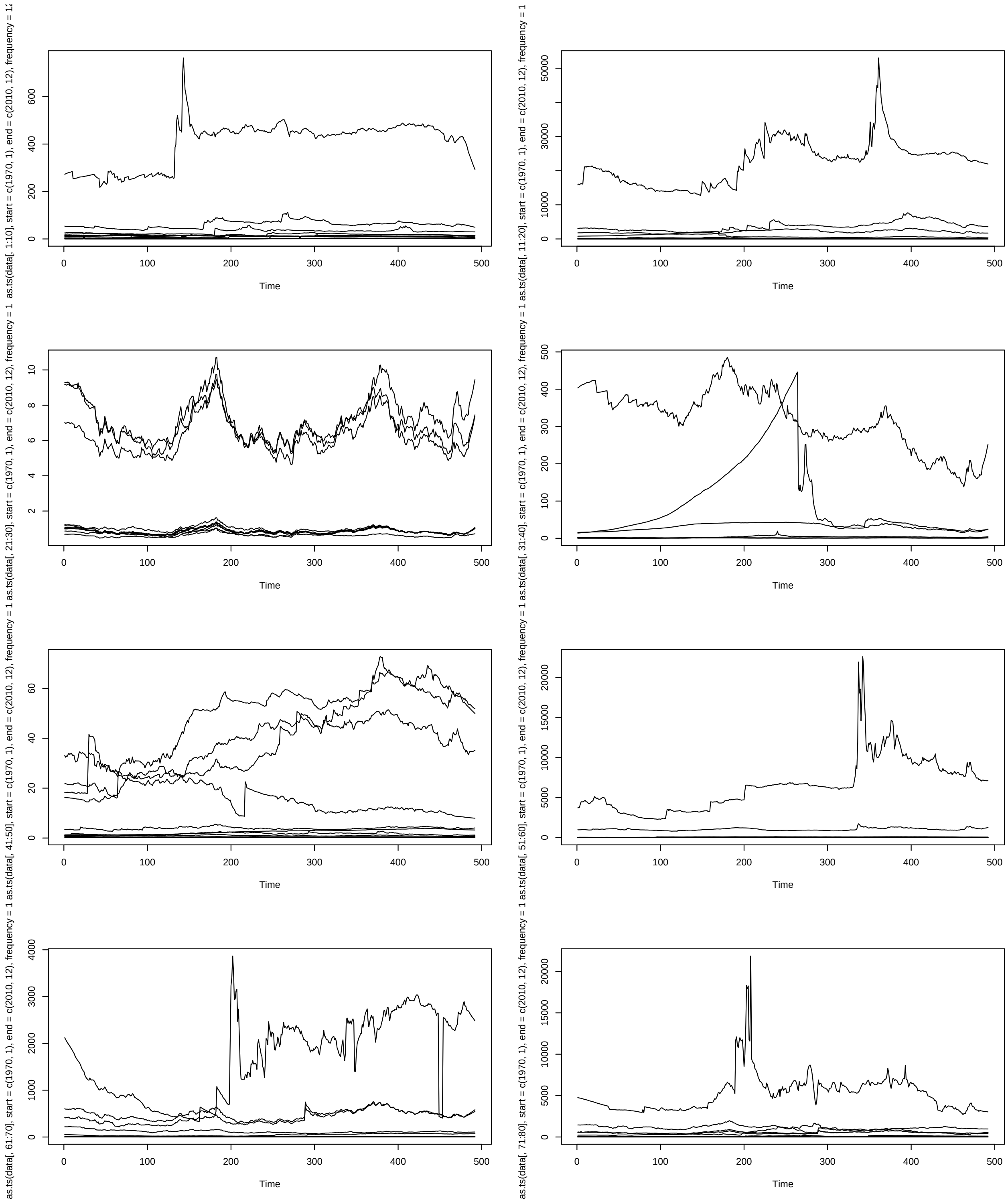
Vemos que países están en la muestra:

```r
# Vemos la lista de países
colnames(data)
```

```
##  [1] "Canada"        "Mexico"        "Guatemala"     "El.Salvador"
##  [5] "Honduras"      "Nicaragua"     "Costa.Rica"    "Panama"
##  [9] "Jamaica"       "Dominican.Rep" "Trin.Tobago"   "Colombia"
## [13] "Venezuela."    "Ecuador"       "Peru"          "Chile"
## [17] "Brazil."       "Paraguay"      "Uruguay"       "Argentina"
## [21] "EU12"          "Sweden"        "Norway"        "Finland"
## [25] "Denmark"       "U.K."          "Ireland"       "Luxembourg"
## [29] "Netherlands"   "France"        "Germany"       "Austria"
## [33] "Czech.Rep"     "Hungary"       "Switzerland"   "Poland"
## [37] "Russia"        "Spain"         "Portugal"      "Italy"
## [41] "Greece"        "Turkey"        "Syria"         "Israel"
## [45] "Jordan"        "Kuwait"        "Saudi.Arabia"  "India"
## [49] "Pakistan"      "Bangladesh"    "Sri.Lanka."    "Thailand"
## [53] "Malaysia"      "Singapore"     "Indonesia"     "Philippines"
## [57] "China.PR"      "Korea"         "Hong.Kong"     "Taiwan"
## [61] "Japan"         "Australia"     "New.Zealand"   "Morocco"
## [65] "Algeria"       "Tunisia"       "Egypt"         "Cameroon"
## [69] "Senegal"       "Sierra.Leone"  "Cote.d.Ivoire" "Ghana"
## [73] "Nigeria"       "Benin"         "Congo"         "Kenya"
## [77] "Tanzania"      "Mozambique"    "South.Africa"  "Zambia"
```

Graficamos las series de tiempo de los países para tener una idea de qué esté pasando.

```r
# SE parte el plot en 8 pedazos
par(mfrow=c(4,2))

# Se grafican series de tiempo de los tipos de cambio
plot.ts(as.ts(data[,1:10],start=c(1970,1),end=c(2010,12),frequency=12),plot.type='single')
plot.ts(as.ts(data[,11:20],start=c(1970,1),end=c(2010,12),frequency=12),plot.type='single')
plot.ts(as.ts(data[,21:30],start=c(1970,1),end=c(2010,12),frequency=12),plot.type='single')
plot.ts(as.ts(data[,31:40],start=c(1970,1),end=c(2010,12),frequency=12),plot.type='single')
plot.ts(as.ts(data[,41:50],start=c(1970,1),end=c(2010,12),frequency=12),plot.type='single')
plot.ts(as.ts(data[,51:60],start=c(1970,1),end=c(2010,12),frequency=12),plot.type='single')
plot.ts(as.ts(data[,61:70],start=c(1970,1),end=c(2010,12),frequency=12),plot.type='single')
plot.ts(as.ts(data[,71:80],start=c(1970,1),end=c(2010,12),frequency=12),plot.type='single')
```



Como era de suponerse, parece haber economías que tienen la misma dinámica en sus tipos de cambios. Además hay economías que sobresalen del resto. Parecería buena idea reducir la dimensión de este conjunto de datos. Probablemente alguno de los factores latentes pueda estar relacionado con el nivel del tipo de cambio y otro con la tendencia.

2.2. Estandarización de datos por media y varianza anual.

Como en componenetes principales, se estandarizan los datos utilizando la media y la varianza anuales.

```
# Extrae el año de cada observación
data$year=as.numeric(format(fechas,"%Y"))

# Se extraen las medias por año por variable
data_mean<-data%>%
  group_by(year)%>%
  summarise_all(mean)

colnames(data_mean)[2:ncol(data_mean)]<-paste("mean",colnames(data_mean)[2:ncol(data_mean)],sep=".")


# Se extraen las desviaciones estándar por año por variable
data_sd<-data%>%
  group_by(year)%>%
  summarise_all(sd)

colnames(data_sd)[2:ncol(data_sd)]<-paste("sd",colnames(data_sd)[2:ncol(data_sd)],sep=".")

# Funcion para estandarizar datos.
estandarizar<-function(country){

  aux<-select(data,year,contains(country))
  aux.mean<-select(data_mean,year,contains(country))
  aux.sd<-select(data_sd,year,contains(country))

  aux<-left_join(aux,aux.mean,by="year")%>%
    left_join(aux.sd,by="year")

  colnames(aux)<-c("year","obs","mean","sd")

  aux<-aux%>%
    mutate(estand=(obs-mean)/sd)

  return(aux$estand)
}

# Se estandariza cada uno de los tipos de cambio con media y varianza anual.
data_estand<-lapply(colnames(data)[1:(ncol(data)-1)],estandarizar)

# Se asignan nombres a los elementos de la lista
names(data_estand)<-colnames(data)[1:(ncol(data)-1)]

# Se convierte a dataframe y se elimina nicaragua.
data_estand<-as_data_frame(data_estand)%>%select(-Nicaragua)
```

3. Inferencia en Análisis de Factores

Pensemos que para cada observación mensual se tiene que

$$\boldsymbol{X}_j|f_j \sim N_p(\boldsymbol{X_j}|\lambda f_j, \boldsymbol{\Sigma}),$$

con $j = 1, \ldots, n = 492$ donde Λ es la matriz de cargas (desconocida), f_j son los factores latentes asociados a la observación j y Σ la matriz diagonal de varianzas (desconocida).

Además, los factores latentes satisfacen que

$$f_j \sim N(f_j|0, I_{k\times k})$$

Marginalmente, las observaciones x_j siguen una distribución normal de la forma

$$x_j|\lambda, \Sigma \sim N(x_i|0, \Omega) \qquad \forall\ j = 1, 2, \cdots, n$$

4. Ejercicio 1: Simulaciones mediante MCMC para 1 factor.

En esta sección se obtiene un análisis de factores para los datos del tipo de cambio utilizando un sólo factor.

4.1. Simulaciones para la posterior de los parámetros

se obtienen 10,000 iteraciones para encontrar la matriz de cargas (en este caso vector de cargas) y el valor de Σ (en este caso matriz diagonal de 80 valores). Notar que no existen restricciones en la matriz de cargas en este caso pues al tener un sólo factor no habrá problemas de identificabilidad.

```
# No de itreaciones
M.sim <- 10000

# periodo de calentamiento
M.burn <- 50

# Calcula la postrior para los datos de swiss
posterior.tc1 <- MCMCfactanal(data_estand,
                              factors=1,
                              lambda.constraints=list(),
                              verbose=0, store.scores=TRUE,
                              a0=1, b0=0.15,
                              data=data,
                              burnin=M.burn, mcmc=M.sim, thin=20,seed=2348)
```

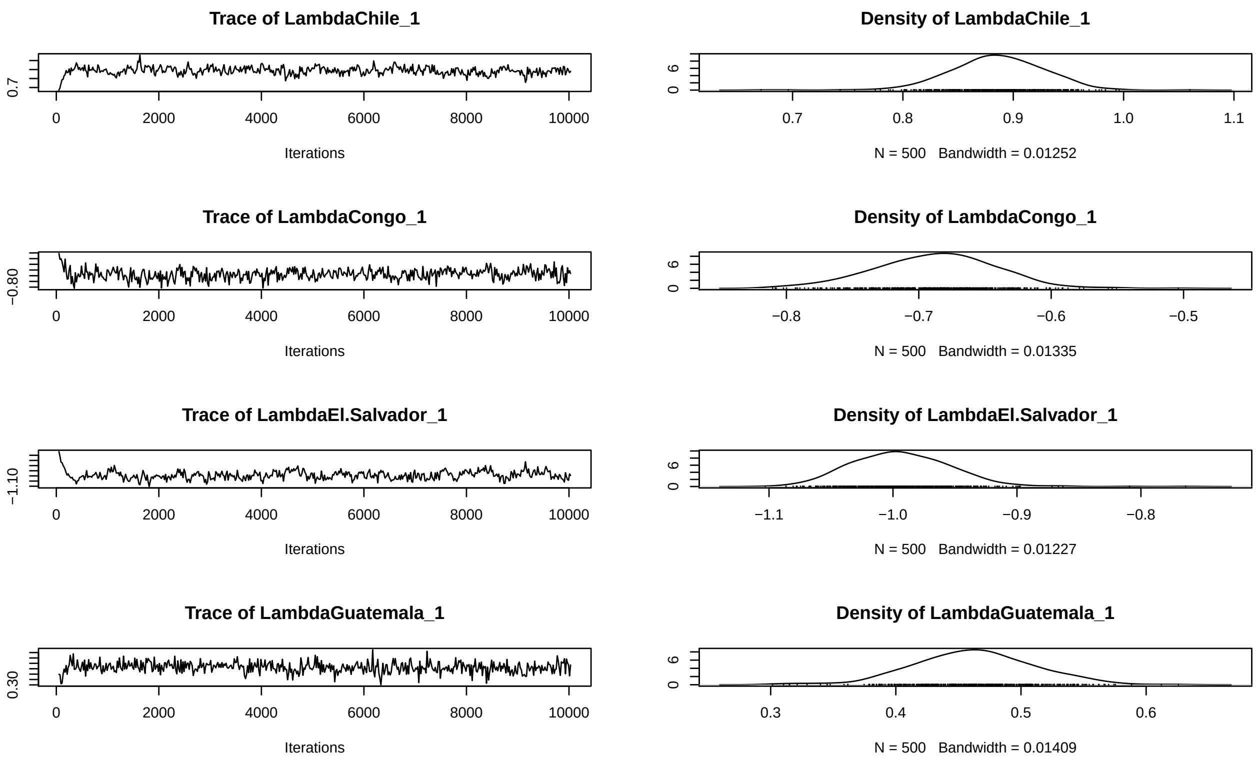
4.2. Resultados de las simulaciones

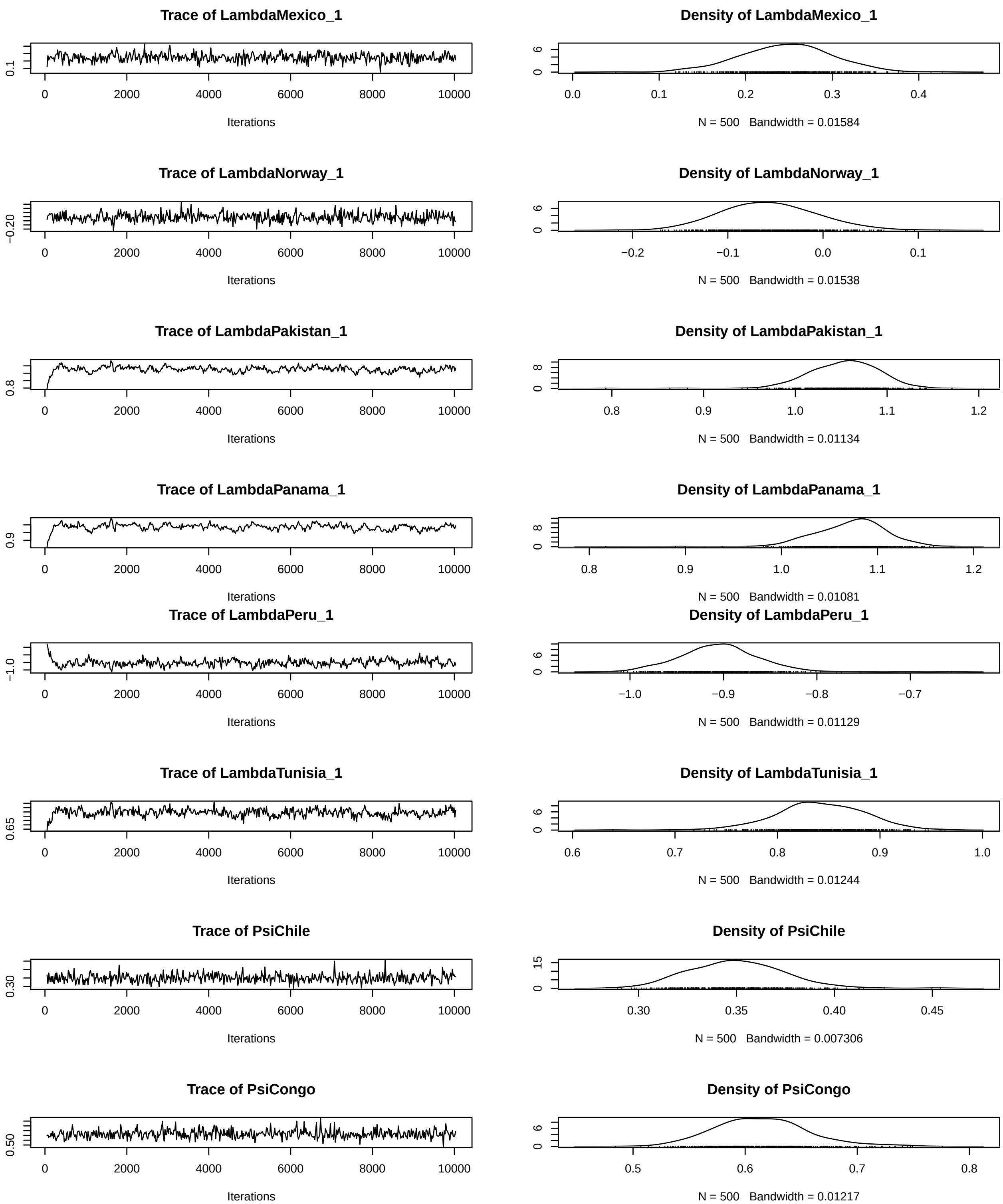
4.2.1. Histograma de los valores simulados para los parámetros

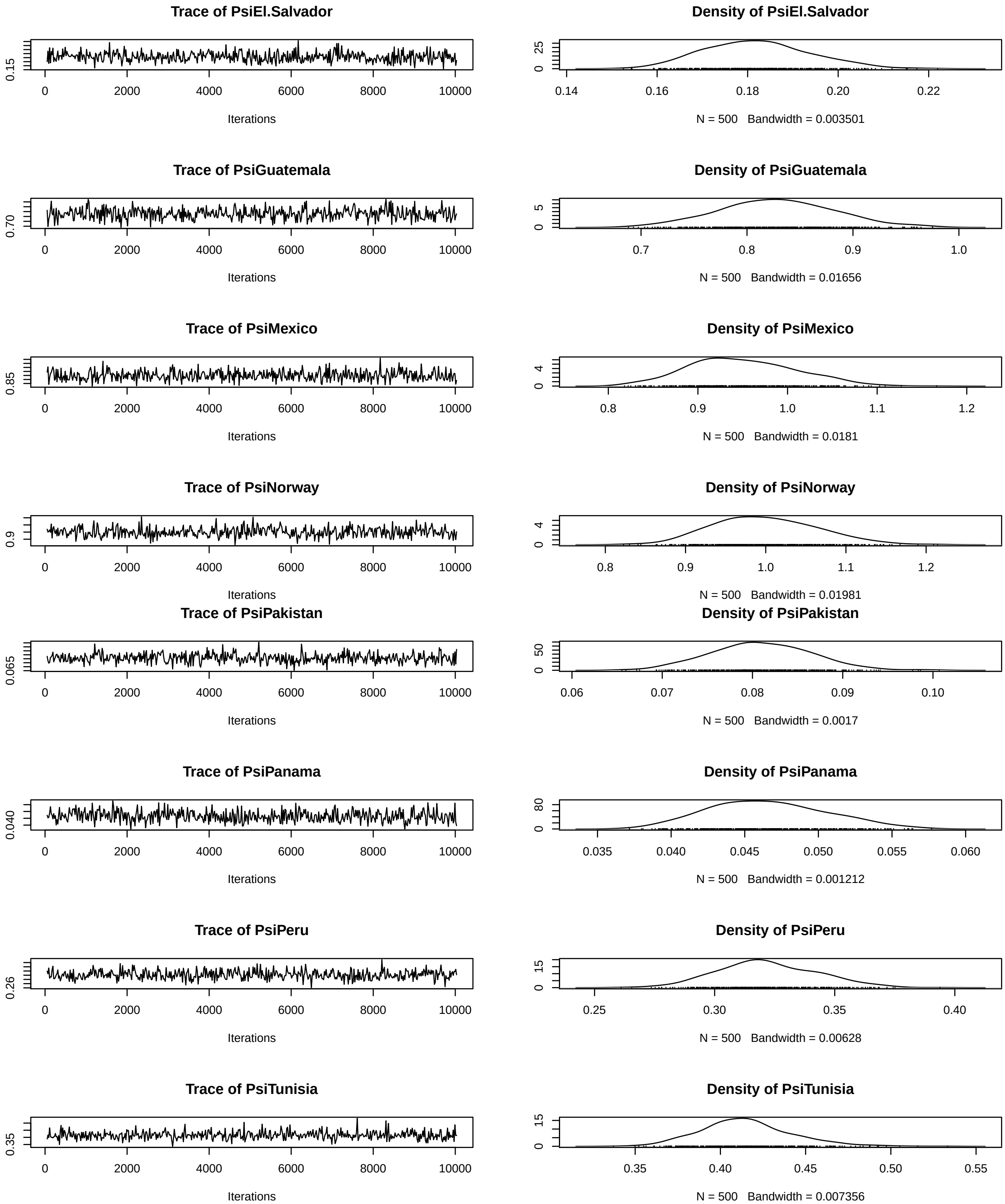
Veamos una muestra de los valores simulados para λ y Σ.

```
# Muestra de 10 países
set.seed(12)
aux<-sort(sample(colnames(data_estand)[2:80],10))
```

```
# Indices para el vector de lambda y para el
# vector de sigma de los paises muestrados
ind1<-match(paste("Lambda",aux,"_1",sep=""),colnames(posterior.tc1))
ind2<-match(paste("Psi",aux,sep=""),colnames(posterior.tc1))

# Grafica de distribuciones
plot(posterior.tc1[,c(ind1,ind2)])
```




Trace of LambdaMexico_1
0.1
0 2000 4000 6000 8000 10000
Iterations
Density of LambdaMexico_1
0 6
0.0 0.1 0.2 0.3 0.4
N = 500 Bandwidth = 0.01584
Trace of LambdaNorway_1
−0.20
0 2000 4000 6000 8000 10000
Iterations
Density of LambdaNorway_1
0 6
−0.2 −0.1 0.0 0.1
N = 500 Bandwidth = 0.01538
Trace of LambdaPakistan_1
0.8
0 2000 4000 6000 8000 10000
Iterations
Density of LambdaPakistan_1
0 8
0.8 0.9 1.0 1.1 1.2
N = 500 Bandwidth = 0.01134
Trace of LambdaPanama_1
0.9
0 2000 4000 6000 8000 10000
Iterations
Density of LambdaPanama_1
0 8
0.8 0.9 1.0 1.1 1.2
N = 500 Bandwidth = 0.01081
Trace of LambdaPeru_1
−1.0
0 2000 4000 6000 8000 10000
Iterations
Density of LambdaPeru_1
0 6
−1.0 −0.9 −0.8 −0.7
N = 500 Bandwidth = 0.01129
Trace of LambdaTunisia_1
0.65
0 2000 4000 6000 8000 10000
Iterations
Density of LambdaTunisia_1
0 6
0.6 0.7 0.8 0.9 1.0
N = 500 Bandwidth = 0.01244
Trace of PsiChile
0.30
0 2000 4000 6000 8000 10000
Iterations
Density of PsiChile
0 15
0.30 0.35 0.40 0.45
N = 500 Bandwidth = 0.007306
Trace of PsiCongo
0.50
0 2000 4000 6000 8000 10000
Iterations
Density of PsiCongo
0 6
0.5 0.6 0.7 0.8
N = 500 Bandwidth = 0.01217



Se puede notar que todas las cadenas son estables, por lo tanto se puede pensar que llegaron a su estado estacionario. En cuanto a la distribuciones de las simulaciones, ésta no es homogénea a lo largo de los diferentes paises muestreados, algunas distribuciones paraecen ser simétricas y otras sesgadas ligeramente a la izquierda o a la derecha.

4.2.2. Resumen de los valores simulados para los parámetros

Veamos el resumen de las simulaciones de los parámetros.

```
resumen1<-summary(posterior.tc1)
```

Para Λ tenemos lo siguiente:

```
resumen.lambda<-cbind(resumen1$statistics[grep("Lambda",rownames(resumen1$statistics)),],
                      resumen1$quantiles[grep("Lambda",rownames(resumen1$quantiles)),])

kable(resumen.lambda,
      format.args=list(size="tiny",scalebox=0.8),
     type='latex',digits=3,
      caption='Resumen de las simulaciones para la matriz de cargas')
```

Tabla 1: Resumen de las simulaciones para la matriz de cargas

	Mean	SD	Naive SE	Time-series SE	2.5 %	25 %	50 %	75 %	97.5 %
LambdaMexico_1	0.247	0.053	0.002	0.003	0.141	0.212	0.247	0.281	0.348
LambdaGuatemala_1	0.462	0.048	0.002	0.003	0.368	0.431	0.463	0.493	0.554
LambdaEl.Salvador_1	-0.993	0.040	0.002	0.004	-1.062	-1.022	-0.995	-0.968	-0.915
LambdaHonduras_1	0.661	0.042	0.002	0.003	0.585	0.631	0.661	0.689	0.744
LambdaCosta.Rica_1	0.779	0.045	0.002	0.004	0.689	0.750	0.780	0.806	0.869
LambdaPanama_1	1.072	0.039	0.002	0.005	0.999	1.049	1.076	1.096	1.139
LambdaJamaica_1	0.623	0.046	0.002	0.003	0.531	0.593	0.626	0.652	0.703
LambdaDominican.Rep_1	0.727	0.045	0.002	0.004	0.643	0.696	0.728	0.755	0.809
LambdaTrin.Tobago_1	-0.190	0.051	0.002	0.002	-0.297	-0.224	-0.190	-0.158	-0.085
LambdaColombia_1	0.754	0.045	0.002	0.003	0.670	0.725	0.754	0.782	0.847
LambdaVenezuela._1	0.427	0.049	0.002	0.003	0.325	0.394	0.428	0.459	0.521
LambdaEcuador_1	0.797	0.043	0.002	0.003	0.717	0.769	0.797	0.824	0.876
LambdaPeru_1	-0.904	0.043	0.002	0.004	-0.985	-0.930	-0.904	-0.881	-0.821
LambdaChile_1	0.886	0.043	0.002	0.004	0.802	0.860	0.886	0.915	0.959
LambdaBrazil._1	0.868	0.044	0.002	0.004	0.779	0.840	0.870	0.897	0.949
LambdaParaguay_1	0.910	0.041	0.002	0.004	0.829	0.885	0.910	0.934	0.987
LambdaUruguay_1	0.068	0.049	0.002	0.002	-0.028	0.036	0.069	0.098	0.167
LambdaArgentina_1	0.657	0.044	0.002	0.003	0.564	0.628	0.660	0.687	0.734
LambdaEU12_1	0.705	0.044	0.002	0.004	0.624	0.675	0.705	0.734	0.795
LambdaSweden_1	0.584	0.050	0.002	0.004	0.486	0.552	0.585	0.616	0.677
LambdaNorway_1	-0.057	0.050	0.002	0.002	-0.147	-0.091	-0.058	-0.023	0.046
LambdaFinland_1	0.159	0.050	0.002	0.002	0.052	0.128	0.161	0.194	0.250
LambdaDenmark_1	-0.289	0.048	0.002	0.002	-0.385	-0.322	-0.288	-0.255	-0.194
LambdaU.K._1	-0.566	0.048	0.002	0.003	-0.659	-0.601	-0.563	-0.533	-0.479
LambdaIreland_1	-0.373	0.048	0.002	0.002	-0.466	-0.406	-0.372	-0.341	-0.279
LambdaLuxembourg_1	0.068	0.049	0.002	0.002	-0.040	0.036	0.070	0.103	0.158
LambdaNetherlands_1	-0.050	0.049	0.002	0.002	-0.150	-0.083	-0.049	-0.016	0.051
LambdaFrance_1	0.081	0.050	0.002	0.002	-0.016	0.050	0.081	0.111	0.178
LambdaGermany_1	0.048	0.049	0.002	0.002	-0.052	0.016	0.047	0.081	0.149
LambdaAustria_1	-0.381	0.050	0.002	0.003	-0.476	-0.414	-0.381	-0.349	-0.288
LambdaCzech.Rep_1	0.183	0.048	0.002	0.002	0.090	0.152	0.181	0.215	0.274
LambdaHungary_1	-0.746	0.044	0.002	0.004	-0.836	-0.774	-0.744	-0.717	-0.663
LambdaSwitzerland_1	-0.495	0.049	0.002	0.003	-0.594	-0.529	-0.496	-0.460	-0.404
LambdaPoland_1	0.655	0.046	0.002	0.004	0.567	0.624	0.650	0.688	0.747
LambdaRussia_1	-0.018	0.049	0.002	0.002	-0.114	-0.052	-0.016	0.016	0.079
LambdaSpain_1	-0.415	0.046	0.002	0.002	-0.502	-0.447	-0.414	-0.385	-0.325

	Mean	SD	Naive SE	Time-series SE	2.5 %	25 %	50 %	75 %	97.5 %
LambdaPortugal_1	-0.470	0.049	0.002	0.003	-0.572	-0.504	-0.465	-0.437	-0.380
LambdaItaly_1	-0.166	0.049	0.002	0.002	-0.266	-0.200	-0.166	-0.131	-0.072
LambdaGreece_1	-0.297	0.050	0.002	0.002	-0.395	-0.332	-0.296	-0.263	-0.203
LambdaTurkey_1	0.316	0.050	0.002	0.003	0.217	0.284	0.317	0.347	0.413
LambdaSyria_1	-0.995	0.041	0.002	0.004	-1.070	-1.021	-0.997	-0.971	-0.917
LambdaIsrael_1	0.267	0.052	0.002	0.003	0.165	0.233	0.268	0.302	0.362
LambdaJordan_1	0.919	0.040	0.002	0.004	0.843	0.893	0.920	0.947	0.992
LambdaKuwait_1	0.964	0.042	0.002	0.004	0.882	0.939	0.968	0.991	1.035
LambdaSaudi.Arabia_1	1.083	0.038	0.002	0.005	1.011	1.061	1.088	1.108	1.146
LambdaIndia_1	1.033	0.040	0.002	0.005	0.960	1.011	1.036	1.059	1.101
LambdaPakistan_1	1.053	0.039	0.002	0.005	0.980	1.029	1.055	1.079	1.121
LambdaBangladesh_1	0.977	0.041	0.002	0.004	0.903	0.952	0.979	1.002	1.047
LambdaSri.Lanka._1	0.715	0.047	0.002	0.004	0.632	0.683	0.716	0.744	0.809
LambdaThailand_1	0.893	0.044	0.002	0.004	0.808	0.867	0.897	0.922	0.970
LambdaMalaysia_1	1.012	0.040	0.002	0.004	0.942	0.988	1.012	1.037	1.087
LambdaSingapore_1	0.308	0.049	0.002	0.002	0.217	0.277	0.305	0.336	0.416
LambdaIndonesia_1	0.899	0.041	0.002	0.004	0.821	0.873	0.900	0.925	0.973
LambdaPhilippines_1	0.703	0.045	0.002	0.004	0.623	0.675	0.704	0.730	0.792
LambdaChina.PR_1	1.032	0.039	0.002	0.004	0.962	1.008	1.034	1.058	1.099
LambdaKorea_1	0.400	0.046	0.002	0.003	0.311	0.368	0.399	0.432	0.488
LambdaHong.Kong_1	0.457	0.048	0.002	0.003	0.372	0.423	0.457	0.486	0.552
LambdaTaiwan_1	-0.099	0.049	0.002	0.002	-0.189	-0.135	-0.100	-0.066	-0.006
LambdaJapan_1	-0.683	0.045	0.002	0.003	-0.764	-0.712	-0.685	-0.656	-0.583
LambdaAustralia_1	0.536	0.045	0.002	0.003	0.452	0.505	0.538	0.566	0.621
LambdaNew.Zealand_1	-0.006	0.048	0.002	0.002	-0.103	-0.036	-0.006	0.024	0.092
LambdaMorocco_1	0.808	0.044	0.002	0.004	0.719	0.779	0.808	0.839	0.891
LambdaAlgeria_1	0.923	0.042	0.002	0.004	0.833	0.895	0.925	0.952	0.999
LambdaTunisia_1	0.842	0.044	0.002	0.004	0.754	0.816	0.841	0.870	0.925
LambdaEgypt_1	0.668	0.044	0.002	0.003	0.579	0.640	0.671	0.698	0.747
LambdaCameroon_1	0.396	0.051	0.002	0.003	0.294	0.362	0.397	0.429	0.500
LambdaSenegal_1	0.823	0.042	0.002	0.004	0.748	0.796	0.825	0.852	0.901
LambdaSierra.Leone_1	0.880	0.044	0.002	0.004	0.792	0.855	0.880	0.905	0.960
LambdaCote.d.Ivoire_1	0.397	0.048	0.002	0.002	0.309	0.365	0.396	0.430	0.495
LambdaGhana_1	0.917	0.044	0.002	0.004	0.838	0.889	0.919	0.947	0.999
LambdaNigeria_1	0.764	0.045	0.002	0.004	0.672	0.737	0.766	0.795	0.849
LambdaBenin_1	0.702	0.046	0.002	0.003	0.607	0.671	0.701	0.731	0.794
LambdaCongo_1	-0.687	0.046	0.002	0.003	-0.779	-0.716	-0.686	-0.658	-0.602
LambdaKenya_1	0.142	0.048	0.002	0.002	0.051	0.110	0.144	0.171	0.229
LambdaTanzania_1	0.898	0.044	0.002	0.004	0.820	0.870	0.896	0.927	0.984
LambdaMozambique_1	1.032	0.040	0.002	0.004	0.952	1.009	1.035	1.056	1.103
LambdaSouth.Africa_1	0.819	0.043	0.002	0.004	0.733	0.790	0.822	0.848	0.898
LambdaZambia_1	0.355	0.047	0.002	0.002	0.265	0.322	0.358	0.389	0.445

Algunos países tienen carga positiva y otros tienen carga negativa. Intuitivamente podría pensarse que este signo está relacionado con el hecho de si la moneda se aprecia o deprecia en el tiempo respecto al dolar.

Veamos cuantos países tienen peso positivo y cuantos tienen peso negativo utilizando la mediana como estimador puntual.

Los países con peso positivo son:

```
lambdas<-resumen1$quantiles[grep("Lambda",rownames(resumen1$quantiles)),3]
```

```r
positivos<-substring(names(lambdas)[which(lambdas>0)],7)
positivos<-substring(positivos, 1, nchar(positivos)-2)

length(positivos)
```

```
## [1] 57
```

```r
positivos
```

```
##  [1] "Mexico"        "Guatemala"     "Honduras"      "Costa.Rica"
##  [5] "Panama"        "Jamaica"       "Dominican.Rep" "Colombia"
##  [9] "Venezuela."    "Ecuador"       "Chile"         "Brazil."
## [13] "Paraguay"      "Uruguay"       "Argentina"     "EU12"
## [17] "Sweden"        "Finland"       "Luxembourg"    "France"
## [21] "Germany"       "Czech.Rep"     "Poland"        "Turkey"
## [25] "Israel"        "Jordan"        "Kuwait"        "Saudi.Arabia"
## [29] "India"         "Pakistan"      "Bangladesh"    "Sri.Lanka."
## [33] "Thailand"      "Malaysia"      "Singapore"     "Indonesia"
## [37] "Philippines"   "China.PR"      "Korea"         "Hong.Kong"
## [41] "Australia"     "Morocco"       "Algeria"       "Tunisia"
## [45] "Egypt"         "Cameroon"      "Senegal"       "Sierra.Leone"
## [49] "Cote.d.Ivoire" "Ghana"         "Nigeria"       "Benin"
## [53] "Kenya"         "Tanzania"      "Mozambique"    "South.Africa"
## [57] "Zambia"
```

Tenemos 57 paises con carga positiva para los factores. No se puede generalizar que un sólo tipo de país tenga cargas positivas, es decir, tenemos tanto países desarrollados (EU, Suecia, Francia, etc) como países en vías de desarrollo (México, Panamá, India, etc), países de LA, Zona Euro, Asia, etc.

Los países con peso negativo son:

```r
negativos<-substring(names(lambdas)[which(lambdas<0)],7)
negativos<-substring(negativos, 1, nchar(negativos)-2)

length(negativos)
```

```
## [1] 21
```

```r
negativos
```

```
##  [1] "El.Salvador" "Trin.Tobago" "Peru"        "Norway"      "Denmark"
##  [6] "U.K."        "Ireland"     "Netherlands" "Austria"     "Hungary"
## [11] "Switzerland" "Russia"      "Spain"       "Portugal"    "Italy"
## [16] "Greece"      "Syria"       "Taiwan"      "Japan"       "New.Zealand"
## [21] "Congo"
```

Se tienen 21 paises con carga negativa. tampoco es posible generalizar que un sólo tipo de país tenga cargas negativas, pero si se puede destacar que son más los países con carga positiva que negativa.

Para Σ tenemos que

```r
resumen.sigma<-cbind(resumen1$statistics[grep("Psi",rownames(resumen1$statistics)),],
                     resumen1$quantiles[grep("Psi",rownames(resumen1$quantiles)),])

kable(resumen.sigma,
      format.args=list(size="tiny",scalebox=0.8),
     type='latex',digits=3,
      caption='Resumen de las simulaciones para la matriz de varianzas $\\Sigma$')
```

Tabla 2: Resumen de las simulaciones para la matriz de varianzas Σ

	Mean	SD	Naive SE	Time-series SE	2.5 %	25 %	50 %	75 %	97.5 %
PsiMexico	0.950	0.059	0.003	0.002	0.840	0.907	0.947	0.990	1.064
PsiGuatemala	0.828	0.054	0.002	0.002	0.723	0.791	0.829	0.863	0.942
PsiEl.Salvador	0.182	0.012	0.001	0.001	0.161	0.174	0.181	0.189	0.206
PsiHonduras	0.640	0.041	0.002	0.002	0.573	0.610	0.636	0.668	0.726
PsiCosta.Rica	0.501	0.033	0.001	0.001	0.438	0.479	0.500	0.522	0.563
PsiPanama	0.047	0.004	0.000	0.000	0.040	0.044	0.046	0.049	0.055
PsiJamaica	0.680	0.043	0.002	0.002	0.600	0.651	0.679	0.707	0.769
PsiDominican.Rep	0.562	0.034	0.002	0.002	0.499	0.541	0.560	0.584	0.629
PsiTrin.Tobago	0.975	0.065	0.003	0.003	0.855	0.931	0.973	1.018	1.109
PsiColombia	0.528	0.035	0.002	0.002	0.467	0.502	0.526	0.551	0.600
PsiVenezuela.	0.849	0.056	0.003	0.003	0.746	0.811	0.846	0.882	0.977
PsiEcuador	0.472	0.031	0.001	0.001	0.420	0.450	0.471	0.494	0.535
PsiPeru	0.322	0.021	0.001	0.001	0.284	0.309	0.320	0.337	0.365
PsiChile	0.350	0.024	0.001	0.001	0.307	0.333	0.349	0.365	0.397
PsiBrazil.	0.376	0.025	0.001	0.001	0.335	0.358	0.375	0.394	0.431
PsiParaguay	0.315	0.020	0.001	0.001	0.279	0.301	0.313	0.329	0.356
PsiUruguay	0.994	0.064	0.003	0.003	0.878	0.947	0.990	1.038	1.126
PsiArgentina	0.643	0.040	0.002	0.002	0.567	0.617	0.640	0.669	0.728
PsiEU12	0.589	0.037	0.002	0.002	0.523	0.564	0.586	0.613	0.664
PsiSweden	0.721	0.044	0.002	0.002	0.641	0.693	0.718	0.746	0.821
PsiNorway	1.000	0.065	0.003	0.003	0.884	0.953	0.996	1.042	1.133
PsiFinland	0.982	0.065	0.003	0.003	0.873	0.934	0.983	1.024	1.112
PsiDenmark	0.932	0.059	0.003	0.003	0.828	0.891	0.932	0.969	1.043
PsiU.K.	0.734	0.048	0.002	0.002	0.654	0.699	0.730	0.765	0.834
PsiIreland	0.887	0.058	0.003	0.002	0.782	0.850	0.885	0.925	1.002
PsiLuxembourg	1.001	0.065	0.003	0.003	0.884	0.955	0.998	1.046	1.135
PsiNetherlands	1.000	0.062	0.003	0.003	0.884	0.959	0.998	1.039	1.126
PsiFrance	0.990	0.060	0.003	0.003	0.884	0.951	0.989	1.030	1.112
PsiGermany	1.003	0.064	0.003	0.003	0.882	0.960	1.001	1.042	1.151
PsiAustria	0.881	0.058	0.003	0.003	0.774	0.841	0.878	0.915	0.992
PsiCzech.Rep	0.973	0.059	0.003	0.003	0.868	0.929	0.970	1.010	1.099
PsiHungary	0.537	0.035	0.002	0.002	0.470	0.511	0.538	0.561	0.606
PsiSwitzerland	0.798	0.053	0.002	0.002	0.698	0.760	0.797	0.835	0.903
PsiPoland	0.649	0.043	0.002	0.002	0.574	0.617	0.644	0.678	0.738
PsiRussia	1.003	0.067	0.003	0.003	0.880	0.957	0.998	1.043	1.138
PsiSpain	0.864	0.056	0.002	0.002	0.760	0.827	0.860	0.896	0.981
PsiPortugal	0.819	0.056	0.003	0.003	0.712	0.781	0.816	0.858	0.932
PsiItaly	0.976	0.066	0.003	0.003	0.859	0.926	0.972	1.018	1.106
PsiGreece	0.926	0.058	0.003	0.003	0.815	0.891	0.926	0.964	1.035
PsiTurkey	0.921	0.061	0.003	0.002	0.810	0.879	0.918	0.962	1.041
PsiSyria	0.179	0.012	0.001	0.001	0.157	0.170	0.178	0.186	0.207
PsiIsrael	0.943	0.063	0.003	0.003	0.825	0.900	0.941	0.983	1.067
PsiJordan	0.300	0.022	0.001	0.001	0.261	0.285	0.298	0.313	0.345
PsiKuwait	0.230	0.014	0.001	0.001	0.205	0.220	0.229	0.240	0.259
PsiSaudi.Arabia	0.027	0.003	0.000	0.000	0.023	0.025	0.027	0.029	0.033
PsiIndia	0.115	0.008	0.000	0.000	0.101	0.110	0.115	0.121	0.132
PsiPakistan	0.081	0.006	0.000	0.000	0.071	0.077	0.081	0.085	0.092
PsiBangladesh	0.207	0.014	0.001	0.001	0.182	0.198	0.207	0.217	0.235
PsiSri.Lanka.	0.577	0.036	0.002	0.002	0.510	0.553	0.575	0.600	0.649
PsiThailand	0.342	0.023	0.001	0.001	0.299	0.326	0.340	0.356	0.392

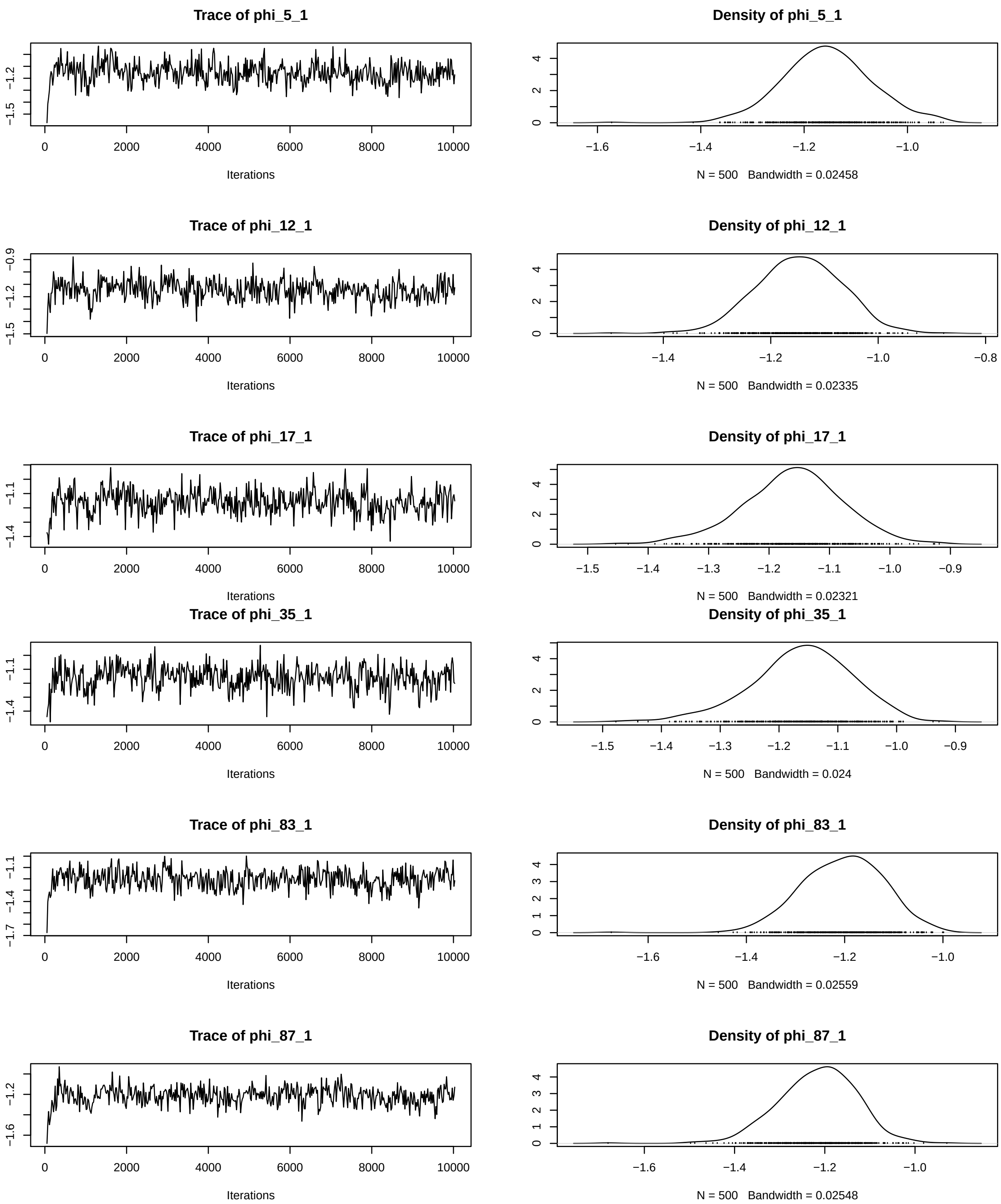
	Mean	SD	Naive SE	Time-series SE	2.5 %	25 %	50 %	75 %	97.5 %
PsiMalaysia	0.155	0.010	0.000	0.000	0.136	0.148	0.154	0.161	0.177
PsiSingapore	0.922	0.058	0.003	0.003	0.815	0.882	0.920	0.962	1.045
PsiIndonesia	0.329	0.021	0.001	0.001	0.289	0.315	0.328	0.343	0.371
PsiPhilippines	0.592	0.037	0.002	0.002	0.518	0.567	0.591	0.615	0.671
PsiChina.PR	0.116	0.008	0.000	0.000	0.103	0.111	0.116	0.121	0.132
PsiKorea	0.868	0.054	0.002	0.003	0.773	0.829	0.866	0.904	0.979
PsiHong.Kong	0.826	0.054	0.002	0.003	0.721	0.790	0.824	0.862	0.941
PsiTaiwan	0.990	0.063	0.003	0.003	0.880	0.947	0.982	1.033	1.114
PsiJapan	0.617	0.040	0.002	0.002	0.543	0.591	0.616	0.643	0.694
PsiAustralia	0.765	0.051	0.002	0.002	0.673	0.729	0.762	0.797	0.866
PsiNew.Zealand	0.995	0.065	0.003	0.003	0.871	0.950	0.996	1.040	1.115
PsiMorocco	0.463	0.030	0.001	0.001	0.406	0.443	0.462	0.482	0.528
PsiAlgeria	0.293	0.020	0.001	0.001	0.257	0.279	0.292	0.307	0.330
PsiTunisia	0.415	0.027	0.001	0.001	0.368	0.398	0.414	0.430	0.472
PsiEgypt	0.636	0.040	0.002	0.002	0.559	0.610	0.634	0.661	0.723
PsiCameroon	0.870	0.055	0.002	0.002	0.769	0.830	0.864	0.906	0.979
PsiSenegal	0.438	0.029	0.001	0.001	0.383	0.418	0.438	0.456	0.501
PsiSierra.Leone	0.358	0.023	0.001	0.001	0.316	0.344	0.357	0.373	0.408
PsiCote.d.Ivoire	0.872	0.053	0.002	0.002	0.771	0.831	0.871	0.906	0.975
PsiGhana	0.308	0.021	0.001	0.001	0.271	0.293	0.307	0.321	0.351
PsiNigeria	0.517	0.032	0.001	0.001	0.457	0.495	0.516	0.537	0.585
PsiBenin	0.593	0.037	0.002	0.002	0.524	0.567	0.594	0.617	0.664
PsiCongo	0.615	0.042	0.002	0.002	0.540	0.587	0.612	0.640	0.713
PsiKenya	0.985	0.063	0.003	0.003	0.867	0.945	0.984	1.024	1.126
PsiTanzania	0.331	0.021	0.001	0.001	0.295	0.316	0.331	0.345	0.376
PsiMozambique	0.119	0.008	0.000	0.000	0.104	0.113	0.118	0.124	0.136
PsiSouth.Africa	0.445	0.027	0.001	0.001	0.394	0.428	0.443	0.463	0.504
PsiZambia	0.896	0.058	0.003	0.002	0.795	0.854	0.893	0.931	1.023

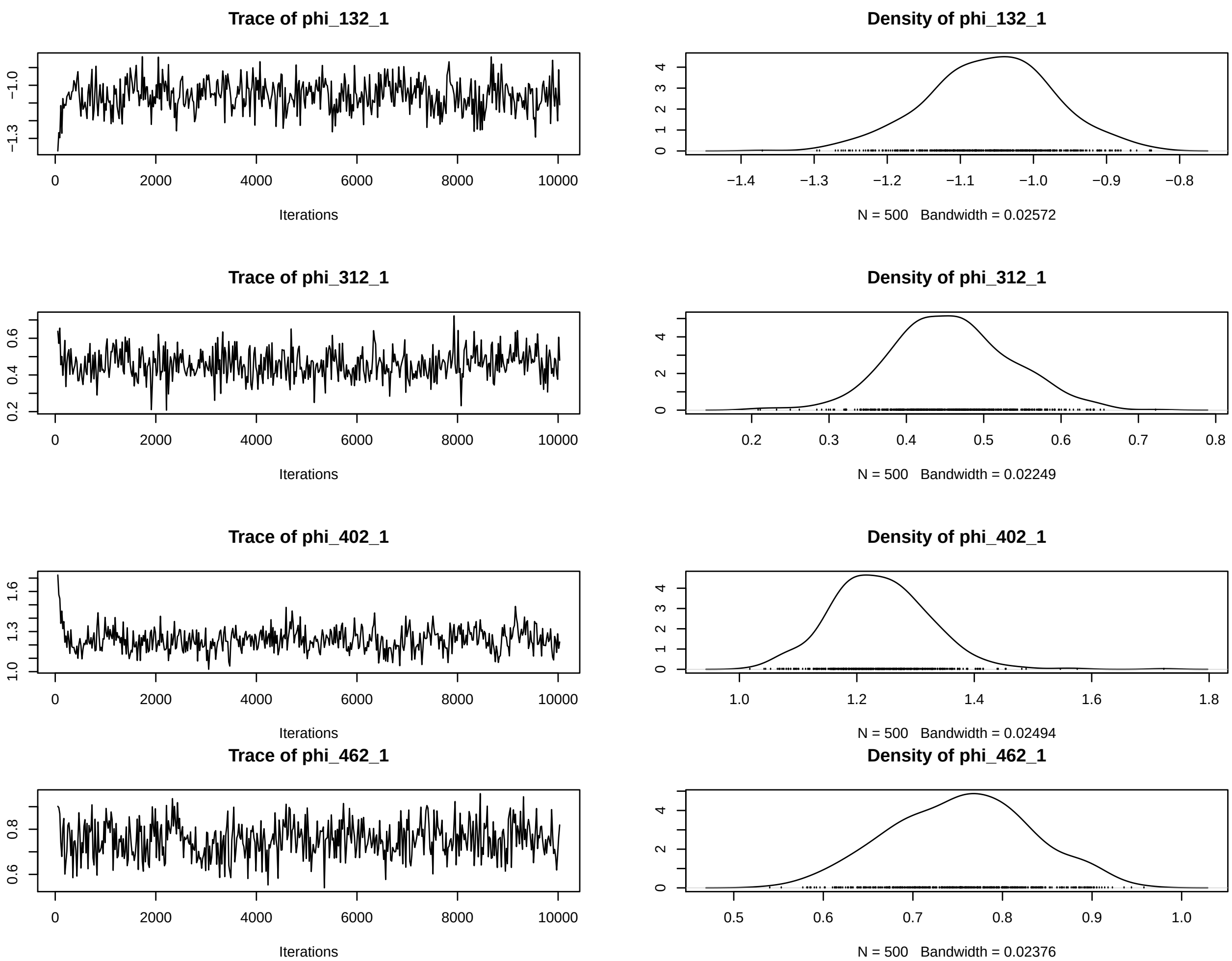
Todas las medias para las simulaciones de los valores de la matriz Σ son positivas (como se esperaba) y varían desde 0.01 hasta 1 aproximadamente.

4.3. Factor Latente

Por último, hagamos un análisis de los factores obtenidos. Veamos la distribución de los valores simulados para los factores para algunas observaciones.

```r
# Muestra de 10 observaciones
set.seed(12)
aux<-sort(sample(1:nrow(data_estand),10))

# Indices para el vector de phi's a examinar
ind<-match(paste("phi_",aux,"_1",sep=""),colnames(posterior.tc1))

# Grafica de distribuciones
plot(posterior.tc1[,ind])
```


Trace of phi_5_1
Iterations
Density of phi_5_1
N = 500 Bandwidth = 0.02458
Trace of phi_12_1
Iterations
Density of phi_12_1
N = 500 Bandwidth = 0.02335
Trace of phi_17_1
Iterations
Density of phi_17_1
N = 500 Bandwidth = 0.02321
Trace of phi_35_1
Iterations
Density of phi_35_1
N = 500 Bandwidth = 0.024
Trace of phi_83_1
Iterations
Density of phi_83_1
N = 500 Bandwidth = 0.02559
Trace of phi_87_1
Iterations
Density of phi_87_1
N = 500 Bandwidth = 0.02548



Todas las cadenas de las simulaciones de los factores parecen estar convirgiendo. Las distribuciones de los factores en cada observación no son centradas y tienen al menos una cola pesada. Se obtienen valoes tanto positivos como negativos para el factor latente.

De hecho, este factor podría pensarse como un índice de los tipos de cambio respecto al dólar a lo largo del tiempo. Veamos los primeros valores simulados.

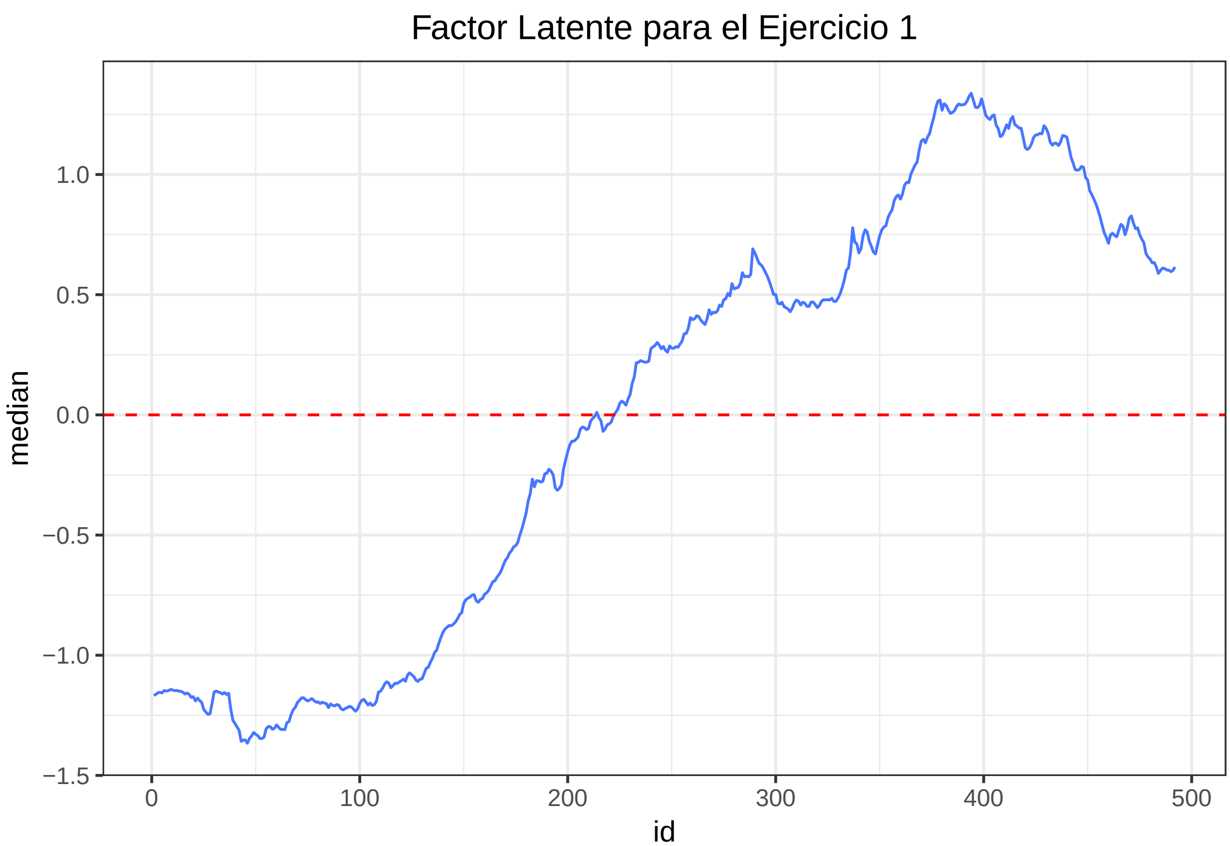
```r
resumen.factores<-cbind(resumen1$statistics[grep("phi",rownames(resumen1$statistics)),],
                        resumen1$quantiles[grep("phi",rownames(resumen1$quantiles)),])

kable(head(resumen.factores,10),
      format.args=list(size="tiny",scalebox=0.8),
     type='latex',digits=3,
      caption='Resumen de las simulaciones para el factor latente')
```

Tabla 3: Resumen de las simulaciones para el factor latente

	Mean	SD	Naive SE	Time-series SE	2.5 %	25 %	50 %	75 %	97.5 %
phi_1_1	-1.173	0.088	0.004	0.006	-1.334	-1.233	-1.167	-1.109	-1.025
phi_2_1	-1.169	0.086	0.004	0.005	-1.337	-1.224	-1.163	-1.113	-1.017
phi_3_1	-1.160	0.084	0.004	0.006	-1.326	-1.215	-1.156	-1.106	-0.997
phi_4_1	-1.153	0.084	0.004	0.005	-1.310	-1.208	-1.154	-1.093	-1.003
phi_5_1	-1.155	0.086	0.004	0.007	-1.321	-1.210	-1.157	-1.102	-0.977
phi_6_1	-1.149	0.086	0.004	0.006	-1.322	-1.200	-1.147	-1.094	-0.979

	Mean	SD	Naive SE	Time-series SE	2.5 %	25 %	50 %	75 %	97.5 %
phi_7_1	-1.151	0.087	0.004	0.007	-1.324	-1.203	-1.149	-1.092	-0.994
phi_8_1	-1.152	0.088	0.004	0.006	-1.320	-1.207	-1.147	-1.093	-0.999
phi_9_1	-1.143	0.081	0.004	0.006	-1.312	-1.195	-1.142	-1.084	-1.005
phi_10_1	-1.144	0.083	0.004	0.005	-1.314	-1.198	-1.144	-1.090	-0.974

```
aux<-data_frame(id=1:nrow(resumen.factores),
                median=resumen.factores[,7])

ggplot(aux,aes(x=id,y=median))+theme_bw()+
  geom_line(color='royalblue1')+geom_hline(yintercept=0,lty=2,col='red')+
  ggtitle('Factor Latente para el Ejercicio 1')+
  theme(plot.title = element_text(hjust=0.5))
```



El factor latente es negativo para los primeros 224 meses de la muestra y positivo después de este punto. La gráfica anterior muestra la serie de tiempo de la mediana del factor latente. Esto refleja que el dólar se apreció respecto al resto de las monedas desde el inicio de la muestra y hasta inicios del 2009 para posteriormente presentar una depreciación hacia el final de la muestra.

5. Ejercicio 2: Simulaciones mediante MCMC para 2 factores.

En esta sección se obtiene un análisis de factores para los datos del tipo de cambio utilizando dos factores.

5.1. Simulaciones para la posterior de los parámetros

Se obtienen 10,000 iteraciones para encontrar la matriz de cargas (en este caso vector de cargas) y el valor de Σ (en este caso matriz diagonal de 80 valores). Notar que sólo se debe imponer una restricción en la matriz de cargas pues ésta tiene 2 columnas.

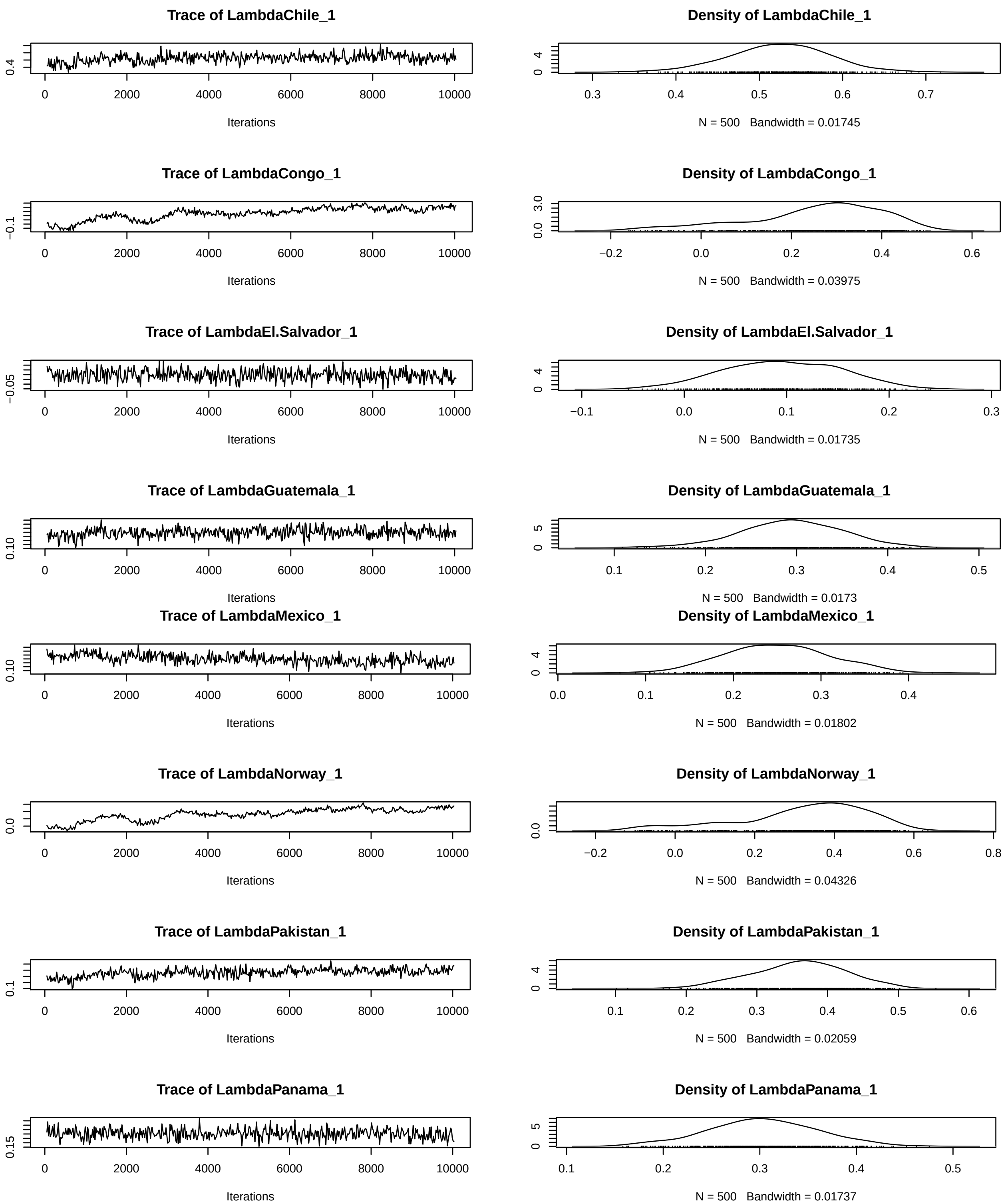
```
# No de itreaciones
M.sim <- 10000

# periodo de calentamiento
M.burn <- 50

# Calcula la postrior para los datos de swiss
posterior.tc2 <- MCMCfactanal(data_estand,
                              factors=2,
                              lambda.constraints=list(Canada=c(2,0)),
                              verbose=0, store.scores=TRUE,
                              a0=1, b0=0.15,
                              data=data_estand,
                              burnin=M.burn, mcmc=M.sim, thin=20,seed=2348)
```

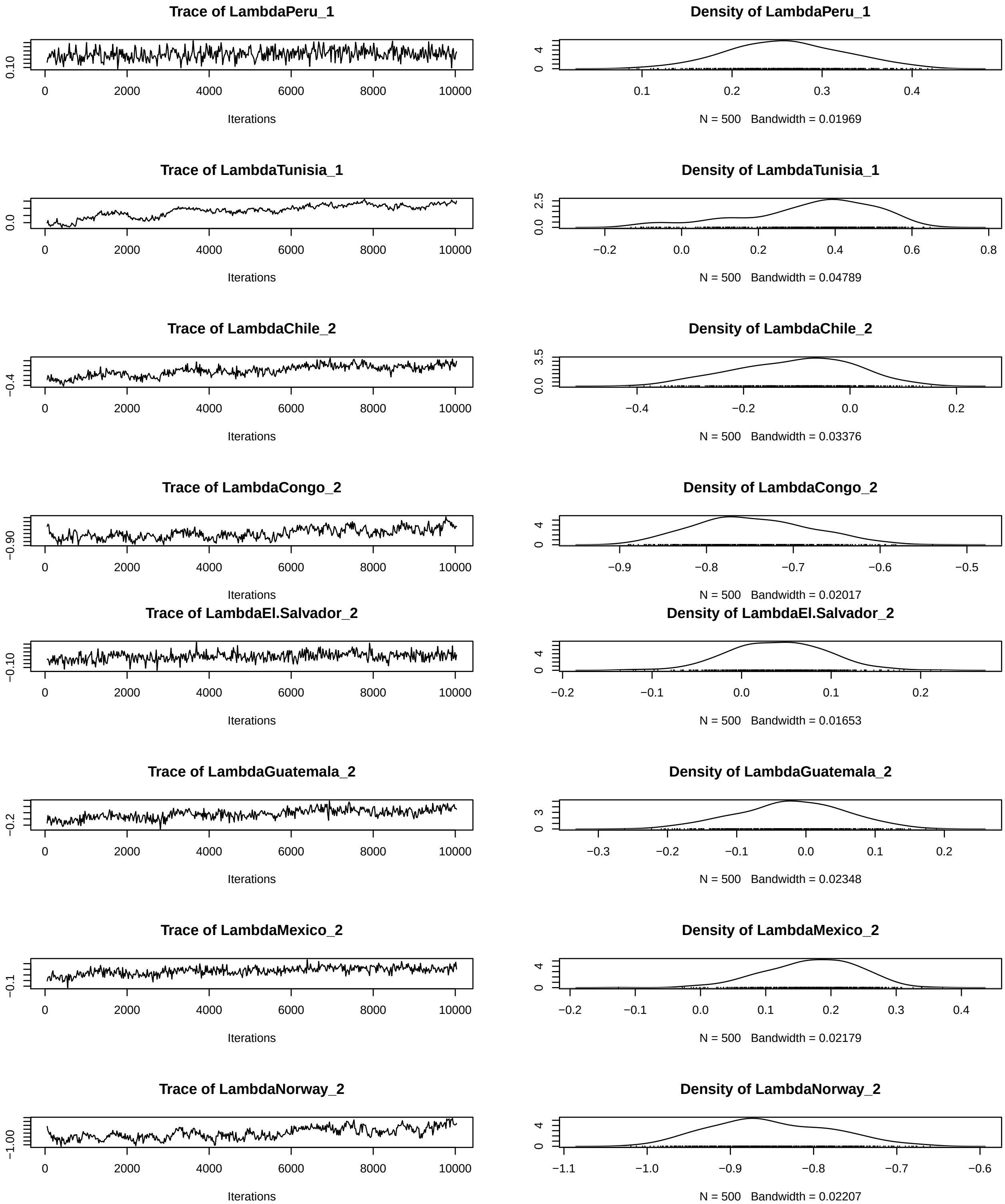
5.2. Resultados de las simulaciones

5.2.1. Histograma de los valores simulados para los parámetros

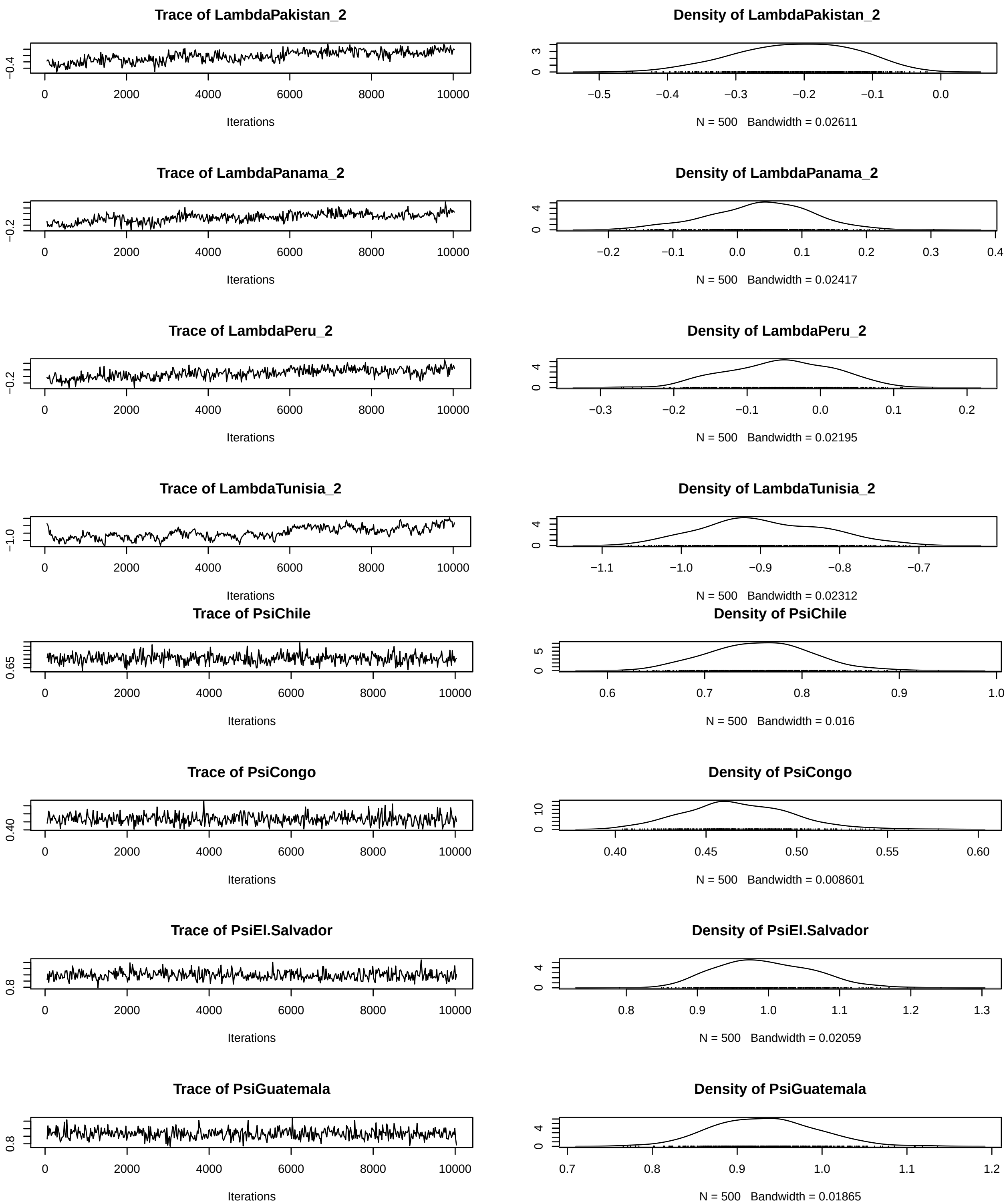
Veamos una muestra de los valores simulados para λ y Σ.

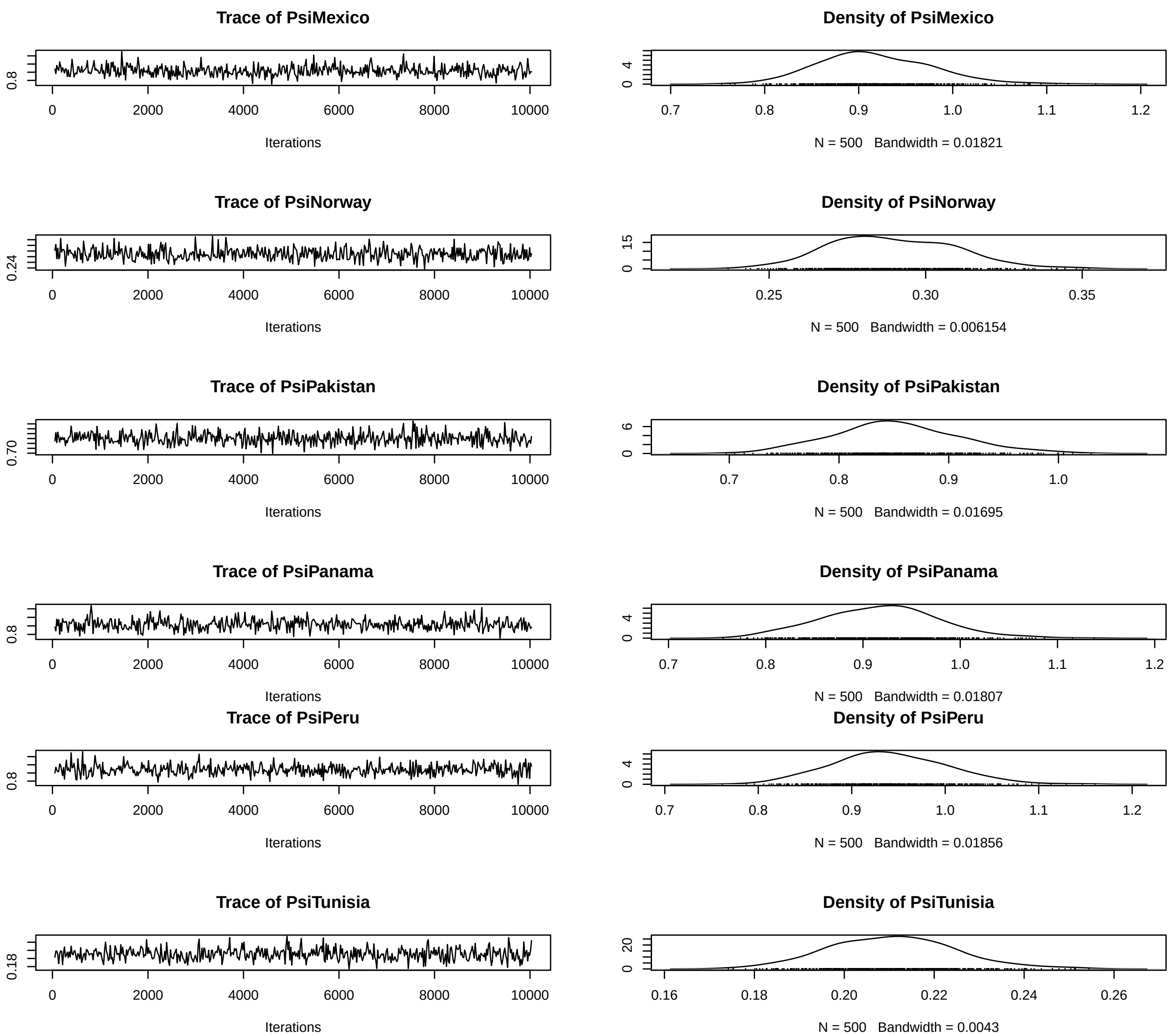
```
# Muestra de 10 países
set.seed(12)

aux<-sort(sample(colnames(data_estand)[2:80],10))

# Indices para el vector de lambda y para el
# vector de sigma de los paises muestrados
ind1<-match(paste("Lambda",aux,"_1",sep=""),colnames(posterior.tc2))
ind2<-match(paste("Lambda",aux,"_2",sep=""),colnames(posterior.tc2))
ind3<-match(paste("Psi",aux,sep=""),colnames(posterior.tc2))

# Grafica de distribuciones
plot(posterior.tc2[,c(ind1,ind2,ind3)])
```


Trace of LambdaChile_1
Iterations
Density of LambdaChile_1
N = 500 Bandwidth = 0.01745
Trace of LambdaCongo_1
Iterations
Density of LambdaCongo_1
N = 500 Bandwidth = 0.03975
Trace of LambdaEl.Salvador_1
Iterations
Density of LambdaEl.Salvador_1
N = 500 Bandwidth = 0.01735
Trace of LambdaGuatemala_1
Iterations
Density of LambdaGuatemala_1
N = 500 Bandwidth = 0.0173
Trace of LambdaMexico_1
Iterations
Density of LambdaMexico_1
N = 500 Bandwidth = 0.01802
Trace of LambdaNorway_1
Iterations
Density of LambdaNorway_1
N = 500 Bandwidth = 0.04326
Trace of LambdaPakistan_1
Iterations
Density of LambdaPakistan_1
N = 500 Bandwidth = 0.02059
Trace of LambdaPanama_1
Iterations
Density of LambdaPanama_1
N = 500 Bandwidth = 0.01737



Trace of LambdaPeru_1
Iterations
Density of LambdaPeru_1
N = 500 Bandwidth = 0.01969
Trace of LambdaTunisia_1
Iterations
Density of LambdaTunisia_1
N = 500 Bandwidth = 0.04789
Trace of LambdaChile_2
Iterations
Density of LambdaChile_2
N = 500 Bandwidth = 0.03376
Trace of LambdaCongo_2
Iterations
Density of LambdaCongo_2
N = 500 Bandwidth = 0.02017
Trace of LambdaEl.Salvador_2
Iterations
Density of LambdaEl.Salvador_2
N = 500 Bandwidth = 0.01653
Trace of LambdaGuatemala_2
Iterations
Density of LambdaGuatemala_2
N = 500 Bandwidth = 0.02348
Trace of LambdaMexico_2
Iterations
Density of LambdaMexico_2
N = 500 Bandwidth = 0.02179
Trace of LambdaNorway_2
Iterations
Density of LambdaNorway_2
N = 500 Bandwidth = 0.02207


Trace of LambdaPakistan_2
Iterations
Density of LambdaPakistan_2
N = 500 Bandwidth = 0.02611
Trace of LambdaPanama_2
Iterations
Density of LambdaPanama_2
N = 500 Bandwidth = 0.02417
Trace of LambdaPeru_2
Iterations
Density of LambdaPeru_2
N = 500 Bandwidth = 0.02195
Trace of LambdaTunisia_2
Iterations
Density of LambdaTunisia_2
N = 500 Bandwidth = 0.02312
Trace of PsiChile
Iterations
Density of PsiChile
N = 500 Bandwidth = 0.016
Trace of PsiCongo
Iterations
Density of PsiCongo
N = 500 Bandwidth = 0.008601
Trace of PsiEl.Salvador
Iterations
Density of PsiEl.Salvador
N = 500 Bandwidth = 0.02059
Trace of PsiGuatemala
Iterations
Density of PsiGuatemala
N = 500 Bandwidth = 0.01865



Se puede notar que no todas todas las cadenas son estables, algunas llegaron a su estado estacionario pero otras muestran tendencia. Sin embargo, esto es en menor medida que cuando se utilizaron los datos no estandarizados. En cuanto a la distribuciones de las simulaciones, esta no es tan homogénea como en el caso anterior. De hecho las cadenas que muestran tendencia son las que presentan "chipotes" en las distribuciones. Podría ser útil aumentar el no. de simulaciones.

5.2.2. Resumen de los valores simulados para los parámetros

Veamos el resumen de las simulaciones de los parámetros.

```
resumen2<-summary(posterior.tc2)
```

Para Λ tenemos lo siguiente:

```
resumen.lambda.1<-cbind(resumen2$statistics[grep(regex("Lambda.+\\_1"),rownames(resumen2$statistics)),]
                        resumen2$quantiles[grep(regex("Lambda.+\\_1"),rownames(resumen2$quantiles)),])

kable(resumen.lambda.1,
      format.args=list(size="tiny",scalebox=0.8),
```

```
    type='latex',digits=3,
     caption='Resumen de las simulaciones para las cargas del primer factor')
```

Tabla 4: Resumen de las simulaciones para las cargas del primer factor

	Mean	SD	Naive SE	Time-series SE	2.5 %	25 %	50 %	75 %	97.5 %
LambdaMexico_1	0.250	0.060	0.003	0.011	0.143	0.210	0.249	0.289	0.366
LambdaGuatemala_1	0.295	0.057	0.003	0.004	0.176	0.257	0.295	0.333	0.406
LambdaEl.Salvador_1	0.096	0.057	0.003	0.003	-0.019	0.056	0.095	0.139	0.200
LambdaHonduras_1	0.065	0.055	0.002	0.002	-0.044	0.026	0.064	0.105	0.164
LambdaCosta.Rica_1	0.242	0.059	0.003	0.006	0.127	0.206	0.240	0.279	0.361
LambdaPanama_1	0.303	0.057	0.003	0.003	0.187	0.265	0.302	0.342	0.411
LambdaJamaica_1	0.223	0.071	0.003	0.010	0.080	0.179	0.223	0.270	0.365
LambdaDominican.Rep_1	0.020	0.055	0.002	0.002	-0.085	-0.021	0.024	0.058	0.123
LambdaTrin.Tobago_1	0.100	0.065	0.003	0.011	-0.041	0.063	0.102	0.144	0.219
LambdaColombia_1	0.541	0.053	0.002	0.002	0.436	0.505	0.542	0.578	0.638
LambdaVenezuela._1	0.070	0.055	0.002	0.003	-0.040	0.035	0.069	0.106	0.181
LambdaEcuador_1	0.298	0.057	0.003	0.003	0.189	0.254	0.301	0.337	0.399
LambdaPeru_1	0.260	0.064	0.003	0.003	0.135	0.216	0.259	0.306	0.388
LambdaChile_1	0.524	0.060	0.003	0.007	0.402	0.485	0.524	0.562	0.640
LambdaBrazil._1	0.439	0.053	0.002	0.002	0.333	0.403	0.437	0.472	0.547
LambdaParaguay_1	0.387	0.056	0.002	0.005	0.286	0.348	0.389	0.424	0.498
LambdaUruguay_1	0.332	0.057	0.003	0.003	0.216	0.296	0.332	0.372	0.439
LambdaArgentina_1	0.453	0.056	0.002	0.005	0.344	0.416	0.451	0.494	0.558
LambdaEU12_1	0.308	0.186	0.008	0.089	-0.121	0.218	0.345	0.446	0.571
LambdaSweden_1	0.319	0.160	0.007	0.072	-0.049	0.239	0.349	0.439	0.543
LambdaNorway_1	0.320	0.163	0.007	0.075	-0.072	0.245	0.352	0.434	0.545
LambdaFinland_1	0.330	0.170	0.008	0.082	-0.069	0.246	0.372	0.449	0.568
LambdaDenmark_1	0.268	0.186	0.008	0.085	-0.170	0.187	0.306	0.407	0.523
LambdaU.K._1	0.344	0.132	0.006	0.066	0.042	0.268	0.369	0.443	0.543
LambdaIreland_1	0.296	0.166	0.007	0.084	-0.084	0.212	0.325	0.420	0.529
LambdaLuxembourg_1	0.307	0.187	0.008	0.091	-0.126	0.217	0.347	0.447	0.561
LambdaNetherlands_1	0.267	0.186	0.008	0.094	-0.167	0.177	0.309	0.406	0.522
LambdaFrance_1	0.258	0.184	0.008	0.094	-0.182	0.169	0.290	0.396	0.509
LambdaGermany_1	0.313	0.187	0.008	0.093	-0.125	0.232	0.353	0.456	0.573
LambdaAustria_1	0.309	0.188	0.008	0.091	-0.139	0.225	0.347	0.449	0.568
LambdaCzech.Rep_1	0.267	0.101	0.005	0.032	0.059	0.200	0.277	0.337	0.447
LambdaHungary_1	0.259	0.106	0.005	0.047	0.031	0.188	0.276	0.341	0.423
LambdaSwitzerland_1	0.172	0.147	0.007	0.071	-0.172	0.092	0.196	0.286	0.377
LambdaPoland_1	0.285	0.078	0.003	0.024	0.119	0.238	0.292	0.338	0.419
LambdaRussia_1	0.245	0.064	0.003	0.003	0.112	0.203	0.245	0.289	0.367
LambdaSpain_1	0.193	0.172	0.008	0.086	-0.194	0.105	0.224	0.320	0.436
LambdaPortugal_1	0.273	0.176	0.008	0.085	-0.119	0.179	0.311	0.403	0.525
LambdaItaly_1	0.292	0.168	0.007	0.077	-0.107	0.209	0.327	0.422	0.520
LambdaGreece_1	0.264	0.153	0.007	0.068	-0.099	0.184	0.301	0.372	0.475
LambdaTurkey_1	0.238	0.094	0.004	0.043	0.021	0.185	0.253	0.305	0.387
LambdaSyria_1	0.129	0.058	0.003	0.006	0.017	0.092	0.129	0.168	0.242
LambdaIsrael_1	0.335	0.110	0.005	0.042	0.094	0.268	0.354	0.420	0.493
LambdaJordan_1	0.317	0.090	0.004	0.027	0.117	0.265	0.331	0.381	0.477
LambdaKuwait_1	0.396	0.091	0.004	0.029	0.194	0.343	0.409	0.452	0.556
LambdaSaudi.Arabia_1	0.438	0.066	0.003	0.003	0.307	0.394	0.437	0.481	0.575
LambdaIndia_1	0.346	0.103	0.005	0.040	0.106	0.292	0.362	0.418	0.520

	Mean	SD	Naive SE	Time-series SE	2.5 %	25 %	50 %	75 %	97.5 %
LambdaPakistan_1	0.359	0.067	0.003	0.016	0.226	0.315	0.363	0.405	0.481
LambdaBangladesh_1	0.338	0.075	0.003	0.022	0.172	0.288	0.347	0.389	0.470
LambdaSri.Lanka._1	0.427	0.060	0.003	0.009	0.309	0.387	0.429	0.473	0.534
LambdaThailand_1	0.415	0.106	0.005	0.047	0.170	0.356	0.432	0.489	0.575
LambdaMalaysia_1	0.650	0.075	0.003	0.026	0.481	0.607	0.660	0.701	0.769
LambdaSingapore_1	0.520	0.119	0.005	0.052	0.238	0.454	0.541	0.606	0.691
LambdaIndonesia_1	0.370	0.066	0.003	0.017	0.226	0.331	0.372	0.417	0.491
LambdaPhilippines_1	0.523	0.059	0.003	0.014	0.395	0.485	0.525	0.564	0.627
LambdaChina.PR_1	0.617	0.064	0.003	0.010	0.479	0.581	0.624	0.659	0.732
LambdaKorea_1	0.186	0.065	0.003	0.012	0.059	0.147	0.190	0.226	0.307
LambdaHong.Kong_1	0.389	0.054	0.002	0.003	0.284	0.353	0.390	0.423	0.492
LambdaTaiwan_1	0.259	0.079	0.004	0.022	0.088	0.210	0.264	0.316	0.393
LambdaJapan_1	0.325	0.110	0.005	0.038	0.077	0.259	0.344	0.403	0.496
LambdaAustralia_1	0.506	0.085	0.004	0.030	0.314	0.465	0.518	0.561	0.648
LambdaNew.Zealand_1	0.518	0.098	0.004	0.038	0.299	0.465	0.537	0.585	0.669
LambdaMorocco_1	0.294	0.165	0.007	0.081	-0.079	0.209	0.328	0.413	0.542
LambdaAlgeria_1	0.313	0.092	0.004	0.030	0.115	0.261	0.325	0.380	0.461
LambdaTunisia_1	0.332	0.172	0.008	0.083	-0.078	0.245	0.373	0.455	0.574
LambdaEgypt_1	0.169	0.057	0.003	0.003	0.049	0.134	0.170	0.208	0.270
LambdaCameroon_1	0.245	0.178	0.008	0.083	-0.154	0.159	0.277	0.379	0.501
LambdaSenegal_1	0.191	0.170	0.008	0.081	-0.196	0.105	0.222	0.316	0.431
LambdaSierra.Leone_1	0.174	0.058	0.003	0.003	0.058	0.135	0.178	0.214	0.286
LambdaCote.d.Ivoire_1	0.211	0.169	0.008	0.084	-0.172	0.118	0.239	0.342	0.462
LambdaGhana_1	0.178	0.053	0.002	0.003	0.077	0.142	0.174	0.213	0.274
LambdaNigeria_1	0.226	0.060	0.003	0.005	0.114	0.184	0.227	0.264	0.346
LambdaBenin_1	0.254	0.162	0.007	0.084	-0.099	0.162	0.280	0.377	0.497
LambdaCongo_1	0.252	0.147	0.007	0.074	-0.095	0.183	0.282	0.357	0.459
LambdaKenya_1	0.419	0.093	0.004	0.034	0.219	0.371	0.431	0.481	0.571
LambdaTanzania_1	0.207	0.060	0.003	0.004	0.087	0.166	0.206	0.248	0.322
LambdaMozambique_1	0.324	0.088	0.004	0.033	0.142	0.269	0.333	0.389	0.476
LambdaSouth.Africa_1	0.385	0.103	0.005	0.041	0.152	0.325	0.397	0.458	0.543
LambdaZambia_1	0.354	0.060	0.003	0.005	0.241	0.316	0.352	0.393	0.467

```r
resumen.lambda.2<-cbind(resumen2$statistics[grep(regex("Lambda.+\\_2"),rownames(resumen2$statistics)),]
                        resumen2$quantiles[grep(regex("Lambda.+\\_2"),rownames(resumen2$quantiles)),])

kable(resumen.lambda.2,
      format.args=list(size="tiny",scalebox=0.8,scalebox=0.8),
     type='latex',digits=3,
      caption='Resumen de las simulaciones para las cargas del segundo factor')
```

Tabla 5: Resumen de las simulaciones para las cargas del segundo factor

	Mean	SD	Naive SE	Time-series SE	2.5 %	25 %	50 %	75 %	97.5 %
LambdaMexico_2	0.171	0.071	0.003	0.023	0.025	0.125	0.175	0.223	0.294
LambdaGuatemala_2	-0.021	0.077	0.003	0.025	-0.179	-0.071	-0.020	0.032	0.124
LambdaEl.Salvador_2	0.041	0.054	0.002	0.004	-0.062	0.003	0.041	0.078	0.151
LambdaHonduras_2	0.023	0.051	0.002	0.003	-0.068	-0.013	0.022	0.054	0.132
LambdaCosta.Rica_2	0.126	0.071	0.003	0.020	-0.023	0.080	0.130	0.173	0.253
LambdaPanama_2	0.034	0.079	0.004	0.027	-0.131	-0.018	0.038	0.090	0.183

	Mean	SD	Naive SE	Time-series SE	2.5 %	25 %	50 %	75 %	97.5 %
LambdaJamaica__2	-0.148	0.066	0.003	0.013	-0.262	-0.193	-0.151	-0.102	-0.025
LambdaDominican.Rep__2	0.021	0.050	0.002	0.002	-0.079	-0.013	0.020	0.058	0.114
LambdaTrin.Tobago__2	-0.174	0.055	0.002	0.005	-0.275	-0.212	-0.173	-0.136	-0.074
LambdaColombia__2	0.029	0.115	0.005	0.044	-0.217	-0.050	0.038	0.112	0.223
LambdaVenezuela.__2	-0.047	0.055	0.002	0.003	-0.148	-0.085	-0.050	-0.007	0.062
LambdaEcuador__2	0.059	0.078	0.003	0.028	-0.092	0.001	0.064	0.121	0.195
LambdaPeru__2	-0.054	0.072	0.003	0.023	-0.184	-0.104	-0.052	0.003	0.073
LambdaChile__2	-0.104	0.110	0.005	0.046	-0.321	-0.182	-0.092	-0.020	0.093
LambdaBrazil.__2	-0.001	0.098	0.004	0.033	-0.217	-0.066	0.008	0.071	0.160
LambdaParaguay__2	-0.054	0.089	0.004	0.027	-0.232	-0.119	-0.044	0.011	0.098
LambdaUruguay__2	-0.035	0.080	0.004	0.028	-0.207	-0.087	-0.032	0.020	0.112
LambdaArgentina__2	-0.081	0.098	0.004	0.035	-0.278	-0.148	-0.071	-0.004	0.078
LambdaEU12__2	-0.981	0.072	0.003	0.017	-1.102	-1.038	-0.992	-0.925	-0.844
LambdaSweden__2	-0.835	0.073	0.003	0.017	-0.970	-0.887	-0.836	-0.783	-0.695
LambdaNorway__2	-0.850	0.072	0.003	0.016	-0.974	-0.904	-0.859	-0.794	-0.706
LambdaFinland__2	-0.883	0.076	0.003	0.020	-1.018	-0.941	-0.888	-0.827	-0.734
LambdaDenmark__2	-0.987	0.066	0.003	0.015	-1.106	-1.033	-0.994	-0.936	-0.856
LambdaU.K.__2	-0.644	0.076	0.003	0.019	-0.776	-0.702	-0.644	-0.591	-0.497
LambdaIreland__2	-0.844	0.072	0.003	0.018	-0.970	-0.895	-0.851	-0.792	-0.704
LambdaLuxembourg__2	-0.992	0.070	0.003	0.017	-1.114	-1.043	-1.001	-0.940	-0.857
LambdaNetherlands__2	-0.995	0.066	0.003	0.014	-1.110	-1.043	-1.001	-0.946	-0.866
LambdaFrance__2	-0.974	0.066	0.003	0.014	-1.095	-1.019	-0.980	-0.923	-0.837
LambdaGermany__2	-0.987	0.073	0.003	0.018	-1.114	-1.041	-0.996	-0.932	-0.839
LambdaAustria__2	-0.993	0.072	0.003	0.017	-1.119	-1.046	-1.000	-0.938	-0.860
LambdaCzech.Rep__2	-0.394	0.071	0.003	0.020	-0.523	-0.444	-0.403	-0.347	-0.250
LambdaHungary__2	-0.511	0.067	0.003	0.017	-0.626	-0.560	-0.514	-0.463	-0.370
LambdaSwitzerland__2	-0.761	0.054	0.002	0.009	-0.862	-0.797	-0.764	-0.726	-0.652
LambdaPoland__2	-0.337	0.070	0.003	0.020	-0.459	-0.390	-0.341	-0.288	-0.199
LambdaRussia__2	0.023	0.070	0.003	0.016	-0.123	-0.022	0.023	0.072	0.164
LambdaSpain__2	-0.908	0.058	0.003	0.012	-1.022	-0.948	-0.912	-0.867	-0.794
LambdaPortugal__2	-0.916	0.068	0.003	0.015	-1.030	-0.966	-0.925	-0.869	-0.775
LambdaItaly__2	-0.869	0.071	0.003	0.020	-0.994	-0.920	-0.878	-0.817	-0.721
LambdaGreece__2	-0.781	0.069	0.003	0.016	-0.903	-0.830	-0.786	-0.732	-0.639
LambdaTurkey__2	-0.430	0.064	0.003	0.015	-0.550	-0.471	-0.429	-0.387	-0.304
LambdaSyria__2	-0.093	0.054	0.002	0.007	-0.203	-0.129	-0.092	-0.057	0.014
LambdaIsrael__2	-0.505	0.078	0.003	0.021	-0.648	-0.564	-0.501	-0.449	-0.358
LambdaJordan__2	-0.377	0.080	0.004	0.024	-0.522	-0.436	-0.379	-0.322	-0.221
LambdaKuwait__2	-0.389	0.086	0.004	0.028	-0.564	-0.451	-0.387	-0.327	-0.240
LambdaSaudi.Arabia__2	0.040	0.096	0.004	0.037	-0.161	-0.020	0.047	0.107	0.203
LambdaIndia__2	-0.449	0.077	0.003	0.024	-0.599	-0.504	-0.453	-0.393	-0.299
LambdaPakistan__2	-0.212	0.085	0.004	0.032	-0.383	-0.273	-0.209	-0.148	-0.062
LambdaBangladesh__2	-0.243	0.081	0.004	0.025	-0.398	-0.299	-0.240	-0.180	-0.094
LambdaSri.Lanka.__2	-0.103	0.096	0.004	0.032	-0.285	-0.174	-0.104	-0.033	0.069
LambdaThailand__2	-0.478	0.091	0.004	0.037	-0.641	-0.547	-0.476	-0.407	-0.306
LambdaMalaysia__2	-0.281	0.130	0.006	0.055	-0.545	-0.374	-0.270	-0.183	-0.060
LambdaSingapore__2	-0.564	0.105	0.005	0.043	-0.756	-0.642	-0.562	-0.486	-0.373
LambdaIndonesia__2	-0.205	0.082	0.004	0.036	-0.367	-0.264	-0.206	-0.140	-0.054
LambdaPhilippines__2	-0.131	0.108	0.005	0.040	-0.353	-0.201	-0.122	-0.044	0.051
LambdaChina.PR__2	-0.117	0.125	0.006	0.052	-0.384	-0.197	-0.102	-0.033	0.100
LambdaKorea__2	-0.225	0.058	0.003	0.015	-0.333	-0.264	-0.230	-0.185	-0.119
LambdaHong.Kong__2	0.013	0.091	0.004	0.031	-0.173	-0.052	0.017	0.087	0.162
LambdaTaiwan__2	-0.275	0.069	0.003	0.023	-0.407	-0.321	-0.277	-0.227	-0.151

	Mean	SD	Naive SE	Time-series SE	2.5 %	25 %	50 %	75 %	97.5 %
LambdaJapan_2	-0.536	0.078	0.003	0.026	-0.681	-0.594	-0.538	-0.478	-0.384
LambdaAustralia_2	-0.341	0.107	0.005	0.040	-0.553	-0.421	-0.339	-0.258	-0.159
LambdaNew.Zealand_2	-0.450	0.109	0.005	0.038	-0.655	-0.539	-0.443	-0.368	-0.258
LambdaMorocco_2	-0.854	0.072	0.003	0.018	-0.977	-0.906	-0.860	-0.802	-0.711
LambdaAlgeria_2	-0.393	0.071	0.003	0.020	-0.522	-0.444	-0.395	-0.339	-0.253
LambdaTunisia_2	-0.895	0.076	0.003	0.018	-1.029	-0.947	-0.900	-0.838	-0.739
LambdaEgypt_2	0.012	0.063	0.003	0.011	-0.115	-0.029	0.016	0.053	0.129
LambdaCameroon_2	-0.931	0.064	0.003	0.014	-1.045	-0.976	-0.937	-0.886	-0.800
LambdaSenegal_2	-0.894	0.058	0.003	0.012	-1.002	-0.936	-0.896	-0.853	-0.781
LambdaSierra.Leone_2	-0.015	0.062	0.003	0.016	-0.133	-0.058	-0.012	0.027	0.110
LambdaCote.d.Ivoire_2	-0.885	0.061	0.003	0.013	-0.994	-0.929	-0.890	-0.842	-0.759
LambdaGhana_2	0.003	0.064	0.003	0.011	-0.135	-0.037	0.002	0.046	0.122
LambdaNigeria_2	0.120	0.069	0.003	0.020	-0.018	0.076	0.124	0.169	0.246
LambdaBenin_2	-0.835	0.068	0.003	0.016	-0.956	-0.883	-0.842	-0.791	-0.693
LambdaCongo_2	-0.746	0.066	0.003	0.015	-0.861	-0.792	-0.751	-0.701	-0.614
LambdaKenya_2	-0.388	0.091	0.004	0.031	-0.570	-0.457	-0.390	-0.317	-0.219
LambdaTanzania_2	-0.062	0.063	0.003	0.011	-0.185	-0.105	-0.060	-0.017	0.054
LambdaMozambique_2	-0.356	0.074	0.003	0.023	-0.502	-0.405	-0.355	-0.304	-0.212
LambdaSouth.Africa_2	-0.467	0.087	0.004	0.026	-0.627	-0.530	-0.473	-0.397	-0.307
LambdaZambia_2	-0.066	0.084	0.004	0.028	-0.235	-0.120	-0.063	-0.007	0.075

Nuevamente se tienen valores positivos y negativos en la matriz de cargas para ambos factores.

Para Σ tenemos que

```
resumen.sigma<-cbind(resumen2$statistics[grep("Psi",rownames(resumen2$statistics)),],
                     resumen2$quantiles[grep("Psi",rownames(resumen2$quantiles)),])

kable(resumen.sigma,
      format.args=list(size="tiny",scalebox=0.8),
     type='latex',digits=3,
      caption='Resumen de las simulaciones para la matriz de varianzas $\\Sigma$')
```

Tabla 6: Resumen de las simulaciones para la matriz de varianzas Σ

	Mean	SD	Naive SE	Time-series SE	2.5 %	25 %	50 %	75 %	97.5 %
PsiMexico	0.917	0.060	0.003	0.003	0.807	0.877	0.912	0.957	1.041
PsiGuatemala	0.932	0.061	0.003	0.003	0.821	0.888	0.931	0.972	1.051
PsiEl.Salvador	0.995	0.067	0.003	0.003	0.882	0.948	0.991	1.044	1.137
PsiHonduras	0.999	0.068	0.003	0.003	0.881	0.955	0.996	1.038	1.150
PsiCosta.Rica	0.939	0.064	0.003	0.003	0.825	0.894	0.937	0.980	1.073
PsiPanama	0.918	0.061	0.003	0.003	0.803	0.876	0.918	0.955	1.040
PsiJamaica	0.946	0.060	0.003	0.003	0.833	0.904	0.943	0.985	1.074
PsiDominican.Rep	0.998	0.062	0.003	0.003	0.881	0.955	0.997	1.037	1.119
PsiTrin.Tobago	0.969	0.061	0.003	0.003	0.866	0.924	0.966	1.009	1.090
PsiColombia	0.752	0.054	0.002	0.002	0.650	0.714	0.748	0.787	0.864
PsiVenezuela.	1.000	0.062	0.003	0.004	0.890	0.956	0.997	1.043	1.120
PsiEcuador	0.927	0.060	0.003	0.003	0.822	0.885	0.922	0.969	1.045
PsiPeru	0.940	0.062	0.003	0.003	0.829	0.900	0.938	0.982	1.059
PsiChile	0.757	0.052	0.002	0.002	0.662	0.720	0.757	0.791	0.866
PsiBrazil.	0.833	0.056	0.003	0.003	0.733	0.793	0.835	0.871	0.947
PsiParaguay	0.870	0.059	0.003	0.003	0.760	0.830	0.865	0.910	0.982

	Mean	SD	Naive SE	Time-series SE	2.5 %	25 %	50 %	75 %	97.5 %
PsiUruguay	0.905	0.060	0.003	0.003	0.800	0.863	0.905	0.943	1.027
PsiArgentina	0.822	0.057	0.003	0.003	0.712	0.781	0.819	0.861	0.936
PsiEU12	0.082	0.006	0.000	0.000	0.071	0.078	0.082	0.086	0.095
PsiSweden	0.311	0.020	0.001	0.001	0.275	0.298	0.310	0.324	0.351
PsiNorway	0.290	0.020	0.001	0.001	0.253	0.274	0.288	0.304	0.331
PsiFinland	0.230	0.015	0.001	0.001	0.201	0.220	0.229	0.240	0.262
PsiDenmark	0.093	0.007	0.000	0.000	0.080	0.088	0.093	0.097	0.106
PsiU.K.	0.543	0.035	0.002	0.002	0.480	0.518	0.541	0.565	0.610
PsiIreland	0.304	0.020	0.001	0.001	0.269	0.290	0.304	0.316	0.343
PsiLuxembourg	0.066	0.005	0.000	0.000	0.057	0.062	0.065	0.069	0.077
PsiNetherlands	0.081	0.006	0.000	0.000	0.071	0.077	0.081	0.085	0.096
PsiFrance	0.121	0.009	0.000	0.000	0.105	0.115	0.120	0.126	0.139
PsiGermany	0.072	0.005	0.000	0.000	0.062	0.069	0.072	0.076	0.083
PsiAustria	0.066	0.005	0.000	0.000	0.057	0.062	0.065	0.069	0.075
PsiCzech.Rep	0.807	0.052	0.002	0.002	0.712	0.772	0.807	0.843	0.904
PsiHungary	0.724	0.047	0.002	0.002	0.638	0.694	0.721	0.750	0.822
PsiSwitzerland	0.475	0.030	0.001	0.001	0.419	0.454	0.472	0.494	0.533
PsiPoland	0.838	0.054	0.002	0.002	0.738	0.799	0.836	0.871	0.956
PsiRussia	0.953	0.064	0.003	0.003	0.834	0.907	0.951	0.998	1.081
PsiSpain	0.252	0.017	0.001	0.001	0.220	0.240	0.252	0.263	0.286
PsiPortugal	0.207	0.014	0.001	0.001	0.183	0.198	0.207	0.217	0.234
PsiItaly	0.275	0.018	0.001	0.001	0.244	0.262	0.274	0.285	0.315
PsiGreece	0.413	0.027	0.001	0.001	0.366	0.395	0.411	0.430	0.469
PsiTurkey	0.799	0.049	0.002	0.002	0.705	0.764	0.798	0.831	0.897
PsiSyria	0.977	0.062	0.003	0.003	0.863	0.935	0.973	1.018	1.104
PsiIsrael	0.684	0.044	0.002	0.002	0.609	0.655	0.678	0.714	0.776
PsiJordan	0.794	0.053	0.002	0.002	0.701	0.756	0.791	0.830	0.896
PsiKuwait	0.739	0.051	0.002	0.002	0.647	0.702	0.738	0.774	0.842
PsiSaudi.Arabia	0.832	0.064	0.003	0.003	0.719	0.786	0.830	0.875	0.961
PsiIndia	0.722	0.046	0.002	0.002	0.640	0.688	0.720	0.749	0.819
PsiPakistan	0.852	0.057	0.003	0.002	0.746	0.816	0.849	0.890	0.976
PsiBangladesh	0.858	0.056	0.003	0.003	0.751	0.819	0.856	0.893	0.974
PsiSri.Lanka.	0.839	0.058	0.003	0.003	0.730	0.800	0.837	0.875	0.964
PsiThailand	0.655	0.042	0.002	0.002	0.579	0.626	0.652	0.679	0.746
PsiMalaysia	0.569	0.042	0.002	0.003	0.491	0.541	0.567	0.594	0.660
PsiSingapore	0.493	0.035	0.002	0.002	0.429	0.469	0.492	0.513	0.570
PsiIndonesia	0.850	0.054	0.002	0.002	0.749	0.813	0.851	0.883	0.964
PsiPhilippines	0.750	0.053	0.002	0.002	0.659	0.713	0.749	0.786	0.860
PsiChina.PR	0.663	0.048	0.002	0.002	0.573	0.632	0.662	0.691	0.762
PsiKorea	0.922	0.058	0.003	0.003	0.811	0.881	0.919	0.962	1.032
PsiHong.Kong	0.868	0.060	0.003	0.003	0.752	0.829	0.865	0.906	0.991
PsiTaiwan	0.883	0.058	0.003	0.003	0.770	0.844	0.884	0.922	0.995
PsiJapan	0.660	0.043	0.002	0.002	0.586	0.628	0.658	0.686	0.747
PsiAustralia	0.679	0.046	0.002	0.002	0.597	0.646	0.679	0.712	0.769
PsiNew.Zealand	0.595	0.040	0.002	0.002	0.525	0.567	0.593	0.619	0.686
PsiMorocco	0.295	0.020	0.001	0.001	0.259	0.281	0.294	0.308	0.335
PsiAlgeria	0.784	0.050	0.002	0.002	0.688	0.749	0.783	0.816	0.884
PsiTunisia	0.211	0.014	0.001	0.001	0.184	0.201	0.211	0.220	0.240
PsiEgypt	0.972	0.062	0.003	0.003	0.855	0.930	0.966	1.010	1.103
PsiCameroon	0.194	0.014	0.001	0.001	0.171	0.185	0.192	0.203	0.225
PsiSenegal	0.279	0.018	0.001	0.001	0.246	0.266	0.277	0.291	0.316
PsiSierra.Leone	0.979	0.063	0.003	0.003	0.866	0.938	0.973	1.021	1.111

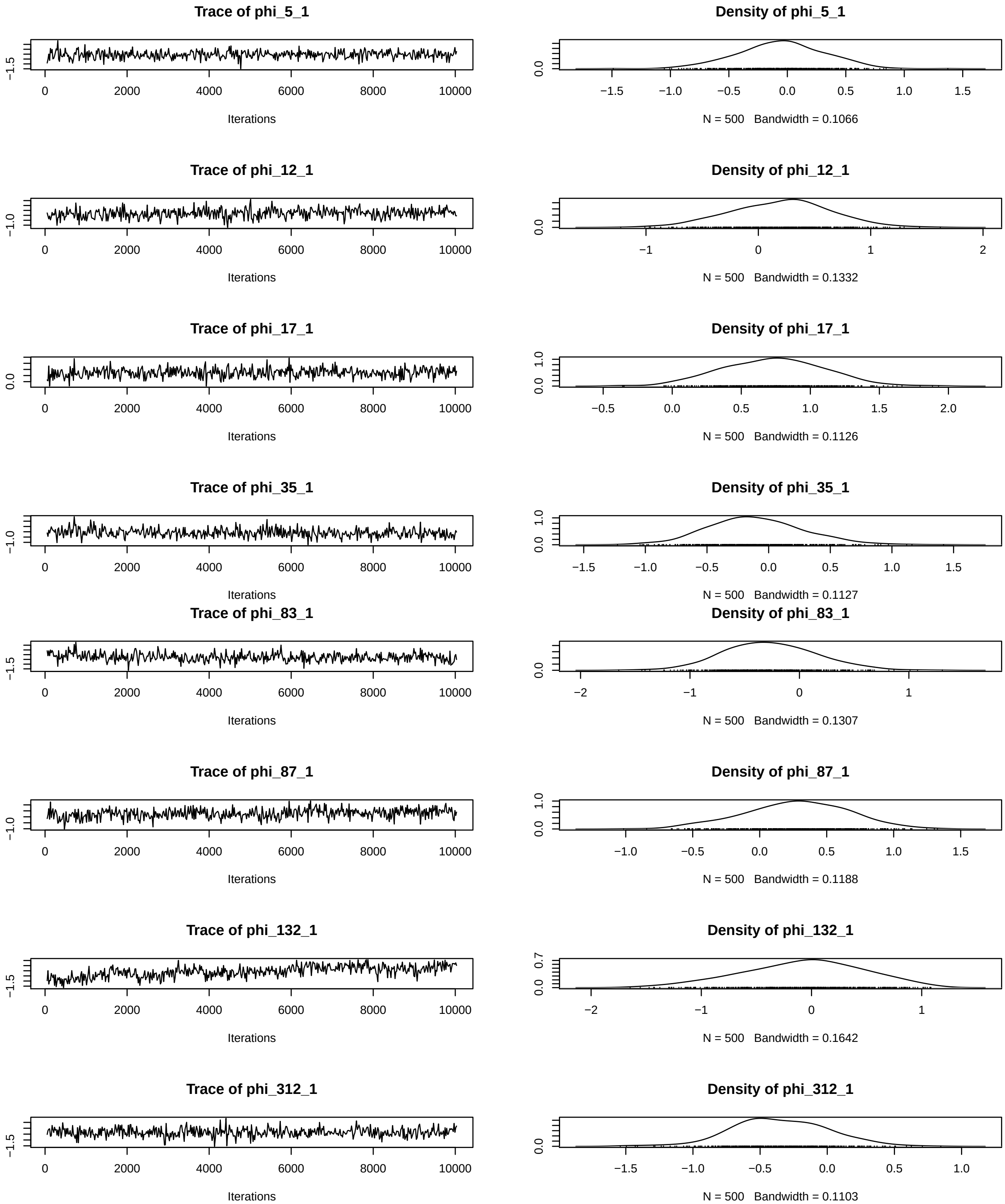
	Mean	SD	Naive SE	Time-series SE	2.5 %	25 %	50 %	75 %	97.5 %
PsiCote.d.Ivoire	0.284	0.019	0.001	0.001	0.251	0.270	0.283	0.296	0.325
PsiGhana	0.972	0.060	0.003	0.003	0.858	0.935	0.969	1.012	1.091
PsiNigeria	0.951	0.062	0.003	0.003	0.831	0.909	0.944	0.991	1.078
PsiBenin	0.339	0.023	0.001	0.001	0.301	0.323	0.337	0.353	0.386
PsiCongo	0.467	0.029	0.001	0.001	0.414	0.449	0.465	0.487	0.527
PsiKenya	0.720	0.045	0.002	0.002	0.643	0.686	0.715	0.750	0.820
PsiTanzania	0.962	0.066	0.003	0.003	0.854	0.918	0.957	1.005	1.110
PsiMozambique	0.797	0.054	0.002	0.002	0.703	0.760	0.793	0.828	0.916
PsiSouth.Africa	0.687	0.045	0.002	0.002	0.604	0.659	0.684	0.716	0.776
PsiZambia	0.894	0.059	0.003	0.003	0.779	0.853	0.891	0.935	1.011

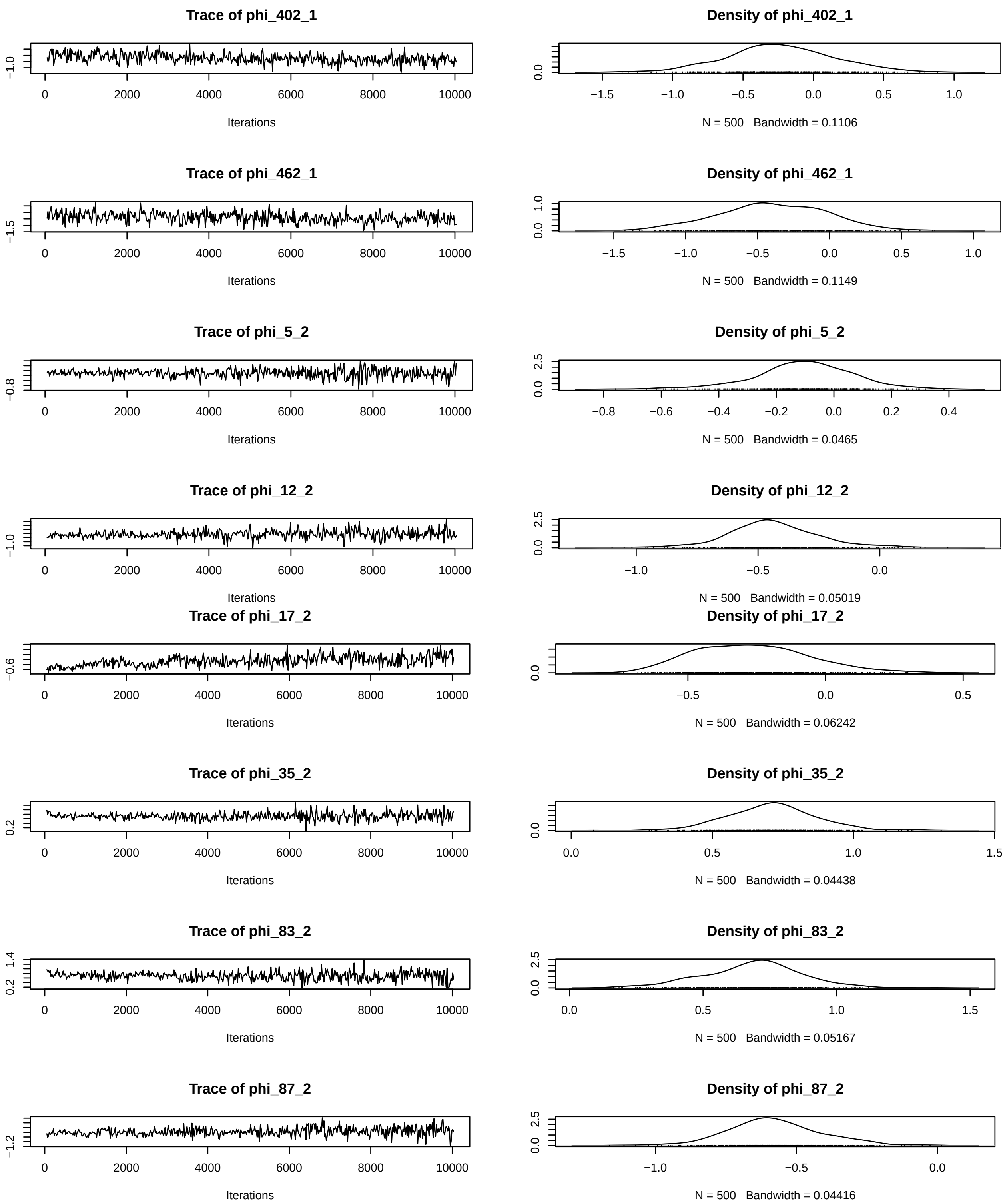
Los valore para Σ van desde 0.01 hasta 1 al igual que en ejercicio 1. Esto era de esperarse pues hay economías con mayor variabilidad en su tipo de cambio.

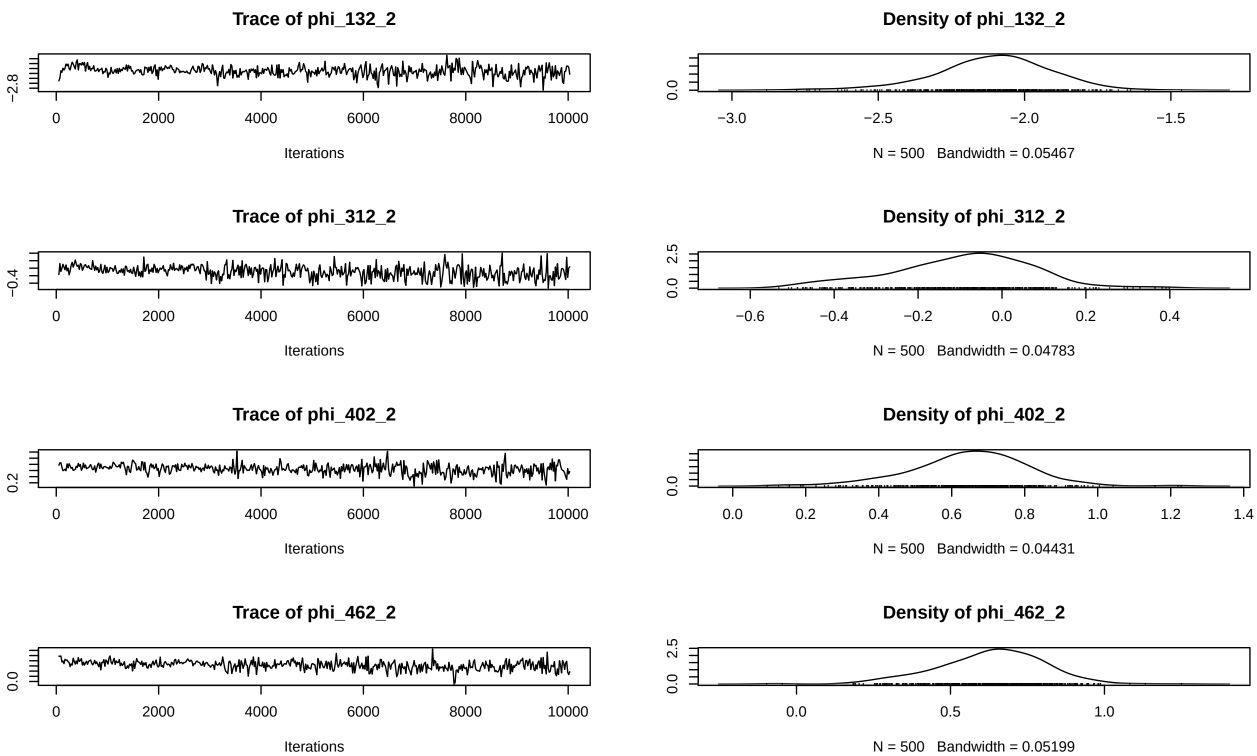
5.3. Factores Latentes

Por último, hagamos un análisis de los factores obtenidos. Veamos la distribución de los valores simulados para los factores para algunas observaciones.

```
# Muestra de 10 observaciones
set.seed(12)
aux<-sort(sample(1:nrow(data_estand),10))

# Indices para el vector de phi's a examinar
ind1<-match(paste("phi_",aux,"_1",sep=""),colnames(posterior.tc2))
ind2<-match(paste("phi_",aux,"_2",sep=""),colnames(posterior.tc2))

# Grafica de distribuciones
plot(posterior.tc2[,c(ind1,ind2)])
```


Trace of phi_5_1
Iterations
Density of phi_5_1
N = 500 Bandwidth = 0.1066
Trace of phi_12_1
Iterations
Density of phi_12_1
N = 500 Bandwidth = 0.1332
Trace of phi_17_1
Iterations
Density of phi_17_1
N = 500 Bandwidth = 0.1126
Trace of phi_35_1
Iterations
Density of phi_35_1
N = 500 Bandwidth = 0.1127
Trace of phi_83_1
Iterations
Density of phi_83_1
N = 500 Bandwidth = 0.1307
Trace of phi_87_1
Iterations
Density of phi_87_1
N = 500 Bandwidth = 0.1188
Trace of phi_132_1
Iterations
Density of phi_132_1
N = 500 Bandwidth = 0.1642
Trace of phi_312_1
Iterations
Density of phi_312_1
N = 500 Bandwidth = 0.1103


Trace of phi_402_1
−1.0
0 2000 4000 6000 8000 10000
Iterations
Density of phi_402_1
0.0
−1.5 −1.0 −0.5 0.0 0.5 1.0
N = 500 Bandwidth = 0.1106
Trace of phi_462_1
−1.5
0 2000 4000 6000 8000 10000
Iterations
Density of phi_462_1
0.0 1.0
−1.5 −1.0 −0.5 0.0 0.5 1.0
N = 500 Bandwidth = 0.1149
Trace of phi_5_2
−0.8
0 2000 4000 6000 8000 10000
Iterations
Density of phi_5_2
0.0 2.5
−0.8 −0.6 −0.4 −0.2 0.0 0.2 0.4
N = 500 Bandwidth = 0.0465
Trace of phi_12_2
−1.0
0 2000 4000 6000 8000 10000
Iterations
Density of phi_12_2
0.0 2.5
−1.0 −0.5 0.0
N = 500 Bandwidth = 0.05019
Trace of phi_17_2
−0.6
0 2000 4000 6000 8000 10000
Iterations
Density of phi_17_2
0.0
−0.5 0.0 0.5
N = 500 Bandwidth = 0.06242
Trace of phi_35_2
0.2
0 2000 4000 6000 8000 10000
Iterations
Density of phi_35_2
0.0
0.0 0.5 1.0 1.5
N = 500 Bandwidth = 0.04438
Trace of phi_83_2
0.2 1.4
0 2000 4000 6000 8000 10000
Iterations
Density of phi_83_2
0.0 2.5
0.0 0.5 1.0 1.5
N = 500 Bandwidth = 0.05167
Trace of phi_87_2
−1.2
0 2000 4000 6000 8000 10000
Iterations
Density of phi_87_2
0.0 2.5
−1.0 −0.5 0.0
N = 500 Bandwidth = 0.04416



Las densidades de los factores son muy distintas entre si, pero se caracterizan por tener al menos una cola pesada e incluso algunas presentan "chipotes". Veamos los primeros valores simulados para cada factor:

```
resumen.factores.1<-cbind(resumen2$statistics[grep(regex("phi.+\\_1"),rownames(resumen2$statistics)),],
                          resumen2$quantiles[grep(regex("phi.+\\_1"),rownames(resumen2$quantiles)),])

kable(head(resumen.factores.1,10),
      format.args=list(size="tiny",scalebox=0.8),
     type='latex',digits=3,
      caption='Resumen de las simulaciones para el primer factor latente')
```

Tabla 7: Resumen de las simulaciones para el primer factor latente

	Mean	SD	Naive SE	Time-series SE	2.5 %	25 %	50 %	75 %	97.5 %
phi_1_1	-1.600	0.453	0.020	0.020	-2.453	-1.910	-1.587	-1.292	-0.737
phi_2_1	-1.411	0.399	0.018	0.018	-2.175	-1.681	-1.397	-1.166	-0.596
phi_3_1	-0.919	0.362	0.016	0.018	-1.577	-1.161	-0.916	-0.684	-0.154
phi_4_1	-0.260	0.412	0.018	0.020	-1.076	-0.550	-0.261	0.015	0.529
phi_5_1	-0.053	0.373	0.017	0.017	-0.801	-0.278	-0.042	0.189	0.635
phi_6_1	0.427	0.349	0.016	0.016	-0.245	0.184	0.424	0.661	1.105
phi_7_1	0.895	0.355	0.016	0.016	0.144	0.638	0.901	1.147	1.519
phi_8_1	0.760	0.363	0.016	0.016	0.012	0.513	0.765	0.999	1.434
phi_9_1	0.825	0.395	0.018	0.018	0.070	0.556	0.817	1.086	1.575
phi_10_1	0.684	0.396	0.018	0.019	-0.075	0.412	0.658	0.955	1.477

```
resumen.factores.2<-cbind(resumen2$statistics[grep(regex("phi.+\\_2"),rownames(resumen2$statistics)),],
                          resumen2$quantiles[grep(regex("phi.+\\_2"),rownames(resumen2$quantiles)),])

kable(head(resumen.factores.2,10),
```

```
    format.args=list(size="tiny",scalebox=0.8),
    type='latex',digits=3,
    caption='Resumen de las simulaciones para el segundo factor latente')
```

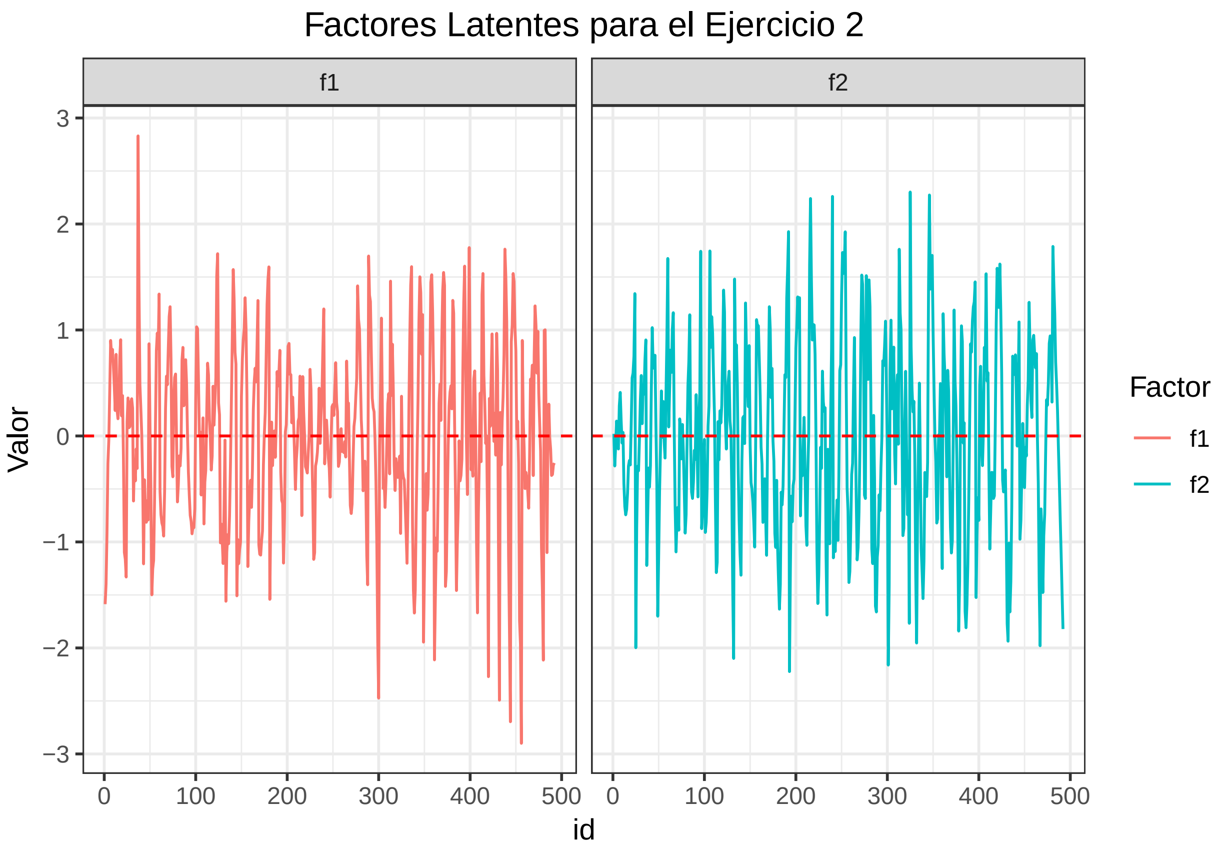
Tabla 8: Resumen de las simulaciones para el segundo factor latente

	Mean	SD	Naive SE	Time-series SE	2.5 %	25 %	50 %	75 %	97.5 %
phi__1__2	0.023	0.364	0.016	0.156	-0.665	-0.231	0.020	0.275	0.734
phi__2__2	-0.278	0.320	0.014	0.122	-0.896	-0.492	-0.283	-0.057	0.352
phi__3__2	-0.095	0.227	0.010	0.081	-0.557	-0.241	-0.097	0.071	0.332
phi__4__2	0.110	0.192	0.009	0.018	-0.306	-0.016	0.140	0.238	0.448
phi__5__2	-0.105	0.172	0.008	0.007	-0.482	-0.199	-0.099	0.005	0.215
phi__6__2	-0.108	0.176	0.008	0.031	-0.411	-0.227	-0.123	0.003	0.280
phi__7__2	0.296	0.236	0.011	0.093	-0.141	0.135	0.286	0.449	0.785
phi__8__2	0.426	0.219	0.010	0.064	0.028	0.271	0.411	0.590	0.871
phi__9__2	0.157	0.232	0.010	0.067	-0.223	-0.011	0.145	0.300	0.658
phi__10__2	-0.047	0.221	0.010	0.054	-0.396	-0.207	-0.066	0.085	0.468

El primer factor tiene valores positivos y negativos a lo largo del periodo muestral y el segundo factor es negativo al inicio y positivo posteriormente.

Graficamos la mediana para analizar los dos factores por completo.

```
aux<-data_frame(id=1:nrow(resumen.factores),
                f1=resumen.factores.1[,7],
                f2=resumen.factores.2[,7])%>%
  gather(Factor, Valor, f1:f2)


ggplot(aux,aes(x=id,y=Valor,color=Factor))+theme_bw()+
  geom_line()+geom_hline(yintercept=0,lty=2,col='red')+
  facet_grid(~Factor)+
  ggtitle('Factores Latentes para el Ejercicio 2')+
  theme(plot.title = element_text(hjust=0.5))
```

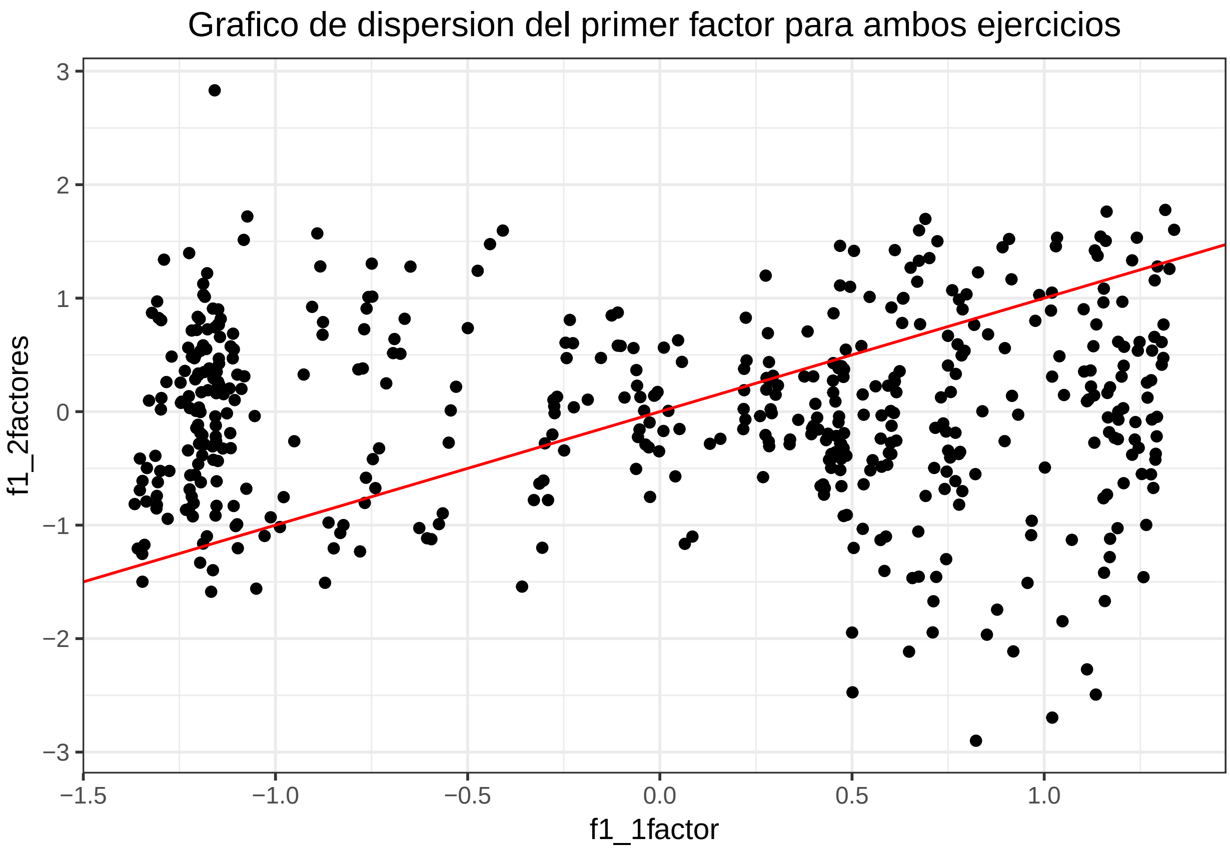


Al estandarizar los datos con la media y desviación estandar anual, los factores simulados se ven completamente diferentes al caso donde no se estandarizaron los datos. Ambos factores parecieran ser ruido blanco.

6. Comparación del primer factor

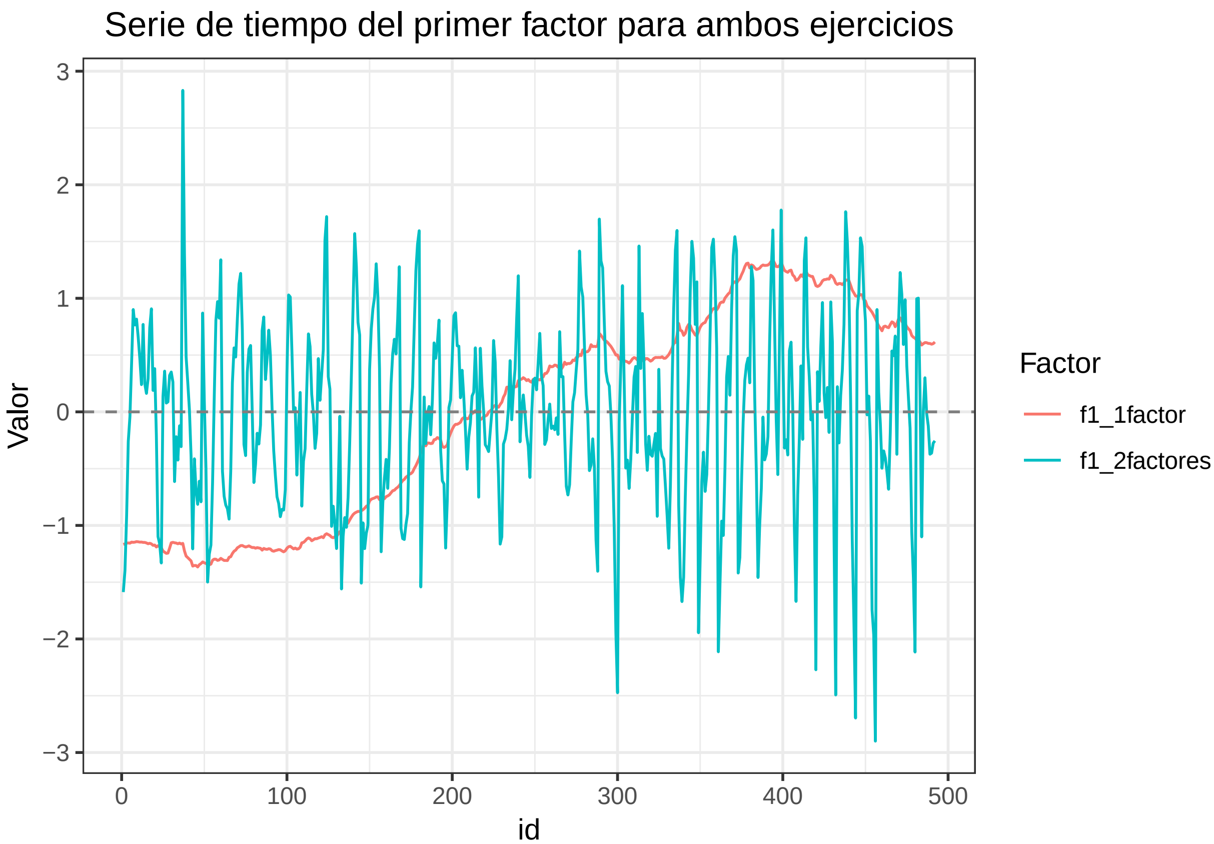
En este apartado comparamos el primer factor del Ejercicio 1 con el primer factor del Ejercicio 2 tomando como estimador puntual la mediana de los factores simulados.

```
plot.f1<-data_frame(f1_1factor=resumen.factores[,7],
                    f1_2factores=resumen.factores.1[,7])

ggplot(plot.f1,aes(x=f1_1factor,y=f1_2factores))+theme_bw()+
  geom_point()+
  geom_abline(slope=1,intercept=0,col='red')+
  ggtitle('Grafico de dispersion del primer factor para ambos ejercicios')+
  theme(plot.title = element_text(hjust=0.5))
```



Claramente, el primer factor del Análsiis de factores con 1 factor y el primer factor del Análisis de Factores con 2 factores no son iguales, de serlo esperaríamos ver los puntos al rededor de la recta de 45 grados. Para las primeras observacioens de la muestra pareciera que el primer factor, del analisis con 1 factor, es menor que el primer factor, del análisis con 2 facotres, y lo contrario ocurre para el final de la muestra.

```
plot.f1<-data_frame(id=1:nrow(resumen.factores),
                    f1_1factor=resumen.factores[,7],
                    f1_2factores=resumen.factores.1[,7])%>%
  gather(Factor, Valor, f1_1factor:f1_2factores)

ggplot(plot.f1,aes(x=id,y=Valor, color=Factor))+theme_bw()+
  geom_line()+
  geom_hline(yintercept=0,col='gray50',lty=2)+
  ggtitle('Serie de tiempo del primer factor para ambos ejercicios')+
  theme(plot.title = element_text(hjust=0.5))
```



En efecto uno de los factores captura mayor variablidad que el otro.