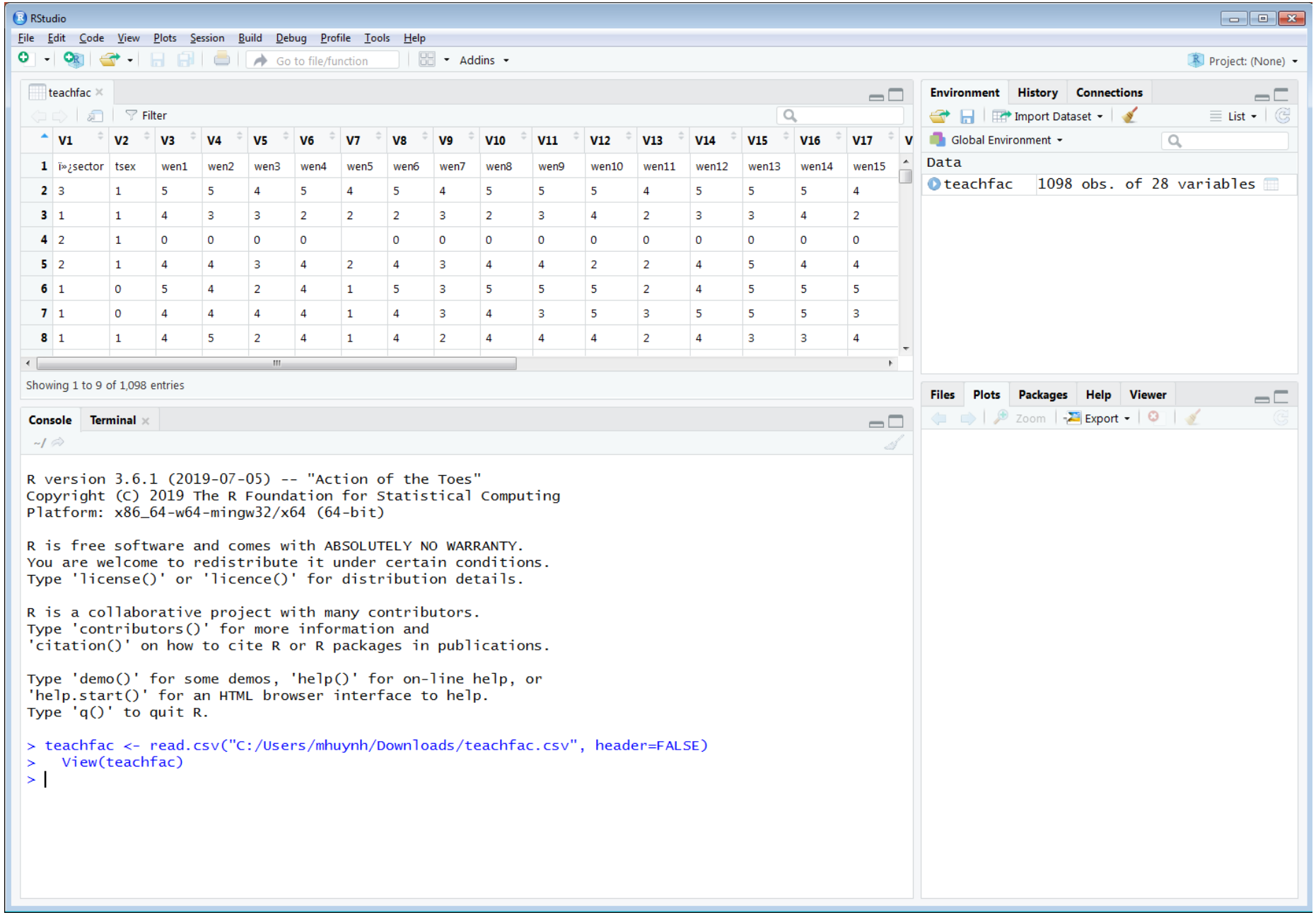
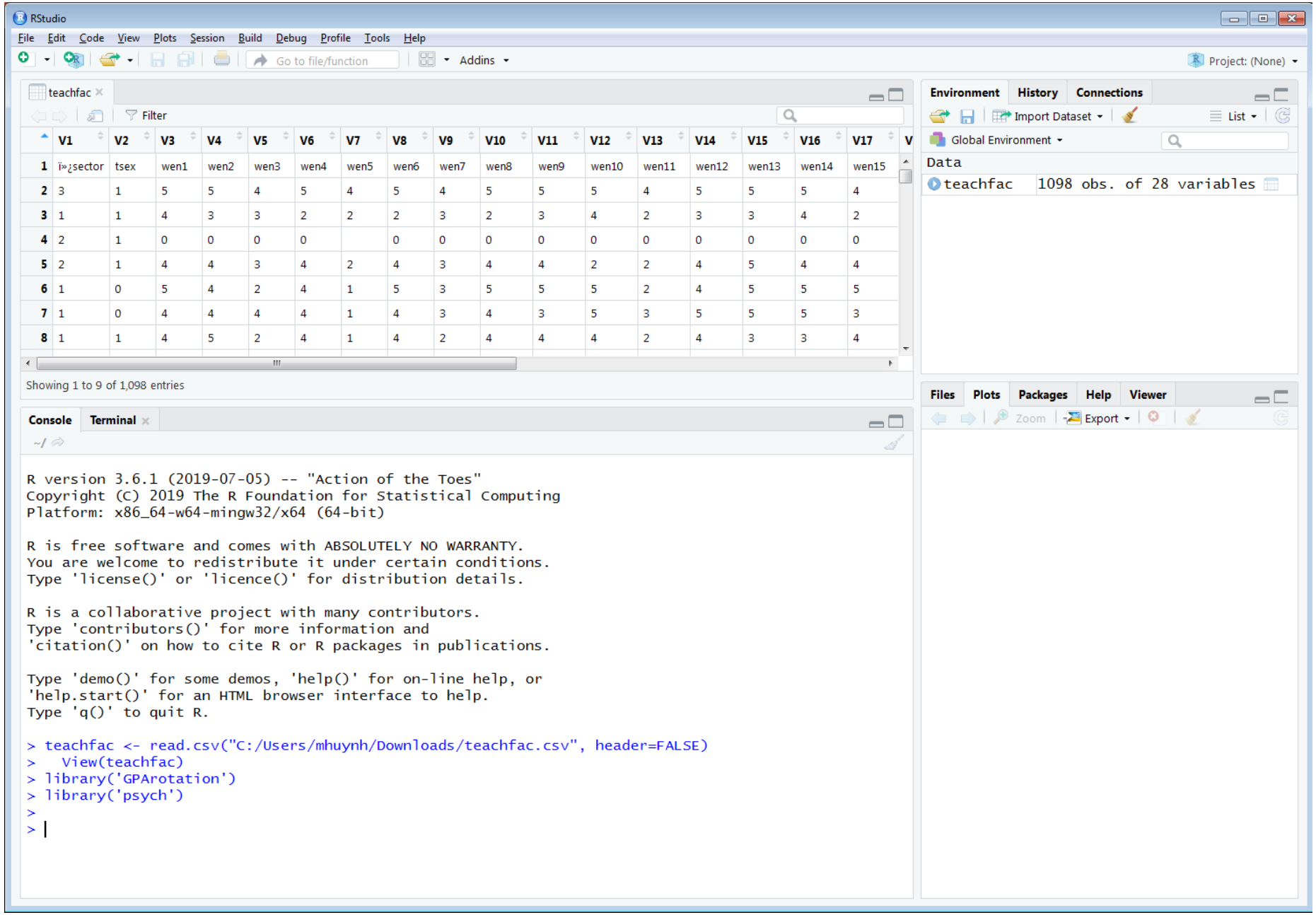
1 Import the Data File (teachfac.csv) from CANVAS



	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12	V13	V14	V15	V16	V17
1	ï»¿sector	tsex	wen1	wen2	wen3	wen4	wen5	wen6	wen7	wen8	wen9	wen10	wen11	wen12	wen13	wen14	wen15
2	3	1	5	5	4	5	4	5	4	5	5	5	4	5	5	5	4
3	1	1	4	3	3	2	2	2	3	2	3	4	2	3	3	4	2
4	2	1	0	0	0	0		0	0	0	0	0	0	0	0	0	0
5	2	1	4	4	3	4	2	4	3	4	4	2	2	4	5	4	4
6	1	0	5	4	2	4	1	5	3	5	5	5	2	4	5	5	5
7	1	0	4	4	4	4	1	4	3	4	3	5	3	5	5	5	3
8	1	1	4	5	2	4	1	4	2	4	4	4	2	4	3	3	4

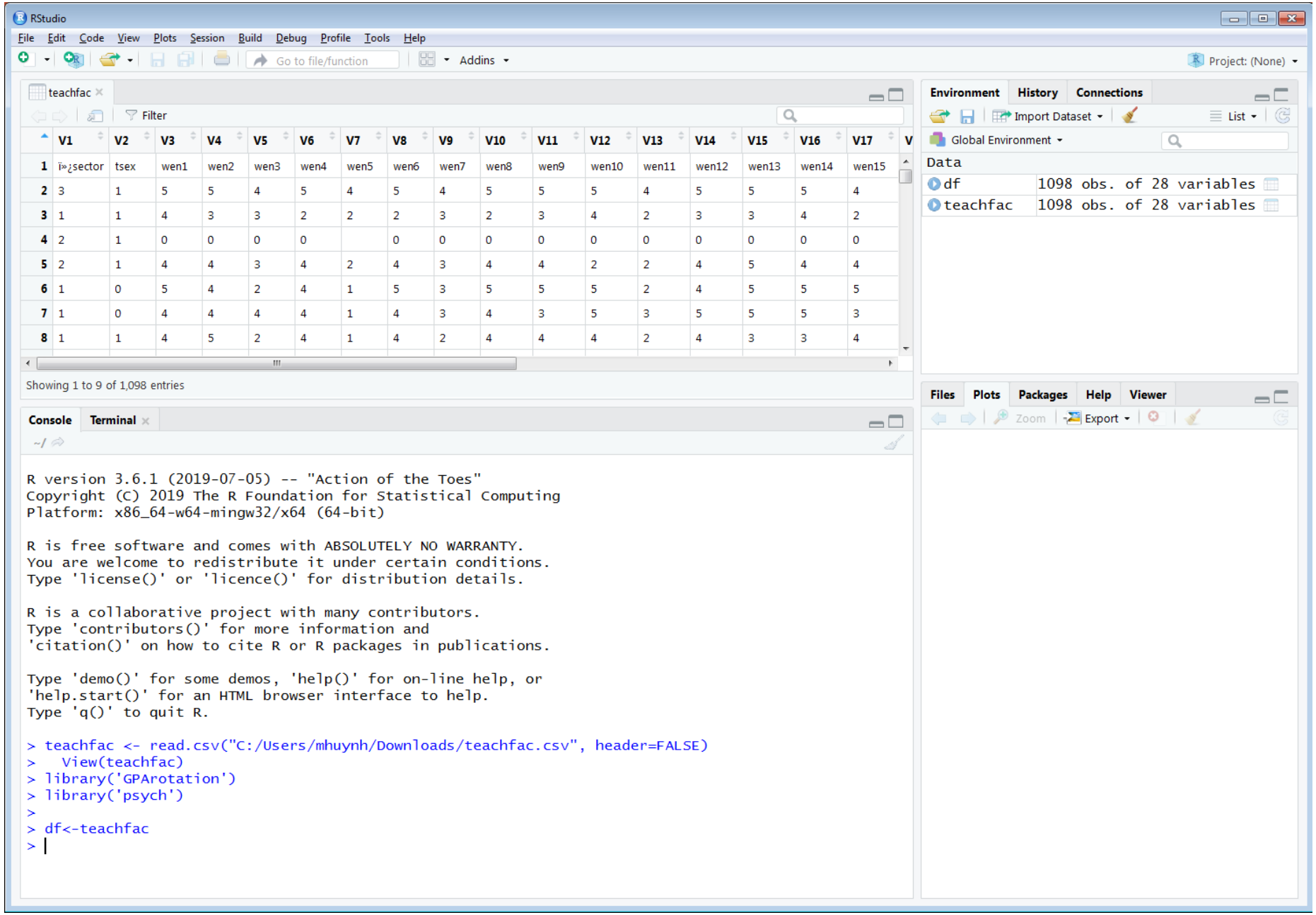
2 Load the necessary packages

```
> library('GPArotation')
> library('psych')
```



3 Define data with suitable name

> df<-teachfac

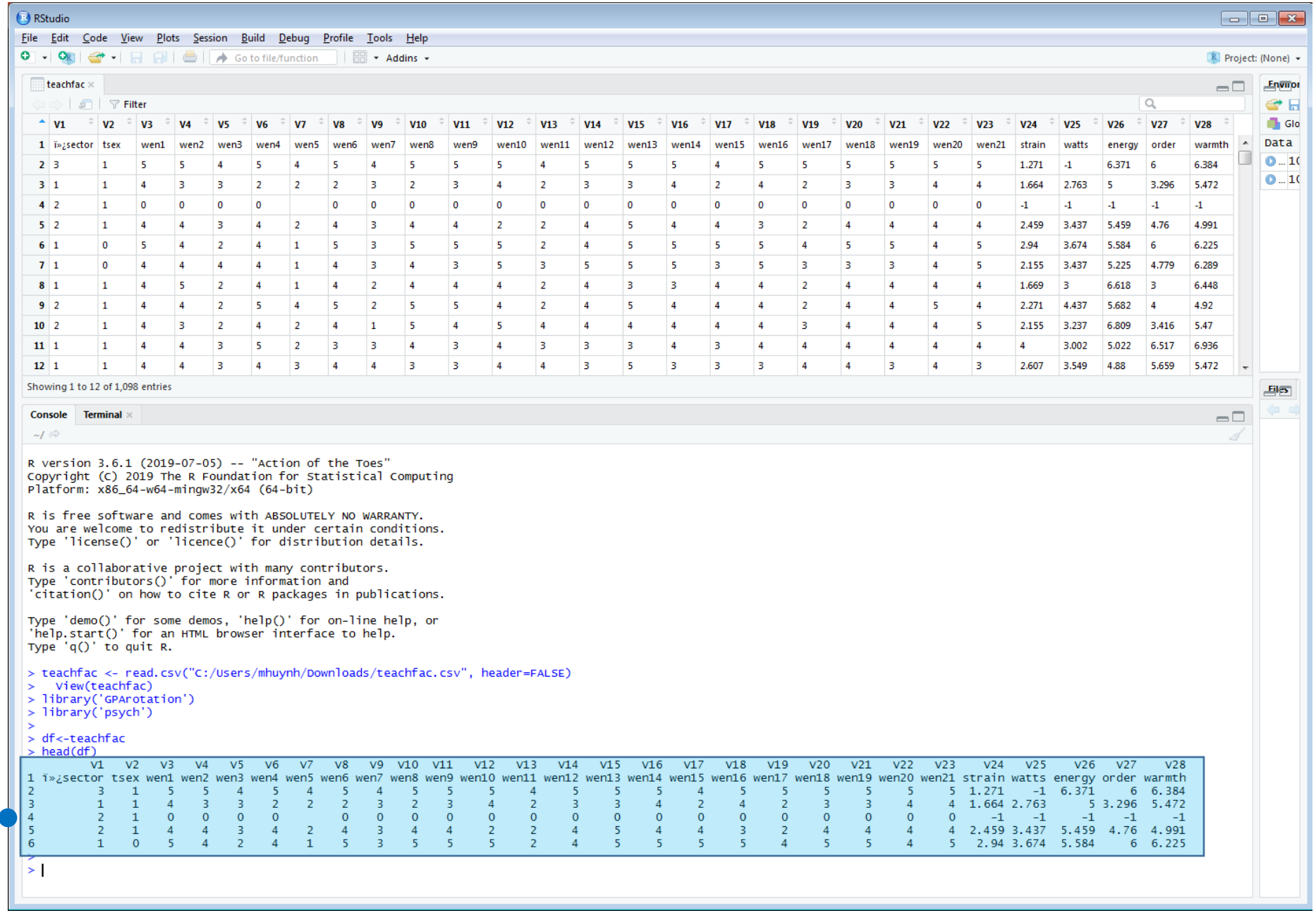


	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12	V13	V14	V15	V16	V17
1	ï»¿sector	tsex	wen1	wen2	wen3	wen4	wen5	wen6	wen7	wen8	wen9	wen10	wen11	wen12	wen13	wen14	wen15
2	3	1	5	5	4	5	4	5	4	5	5	5	4	5	5	5	4
3	1	1	4	3	3	2	2	2	3	2	3	4	2	3	3	4	2
4	2	1	0	0	0	0		0	0	0	0	0	0	0	0	0	0
5	2	1	4	4	3	4	2	4	3	4	4	2	2	4	5	4	4
6	1	0	5	4	2	4	1	5	3	5	5	5	2	4	5	5	5
7	1	0	4	4	4	4	1	4	3	4	3	5	3	5	5	5	3
8	1	1	4	5	2	4	1	4	2	4	4	4	2	4	3	3	4

4 Inspect the current data frame

> head(df)

This reveals the data frame to consists of 28 variables:



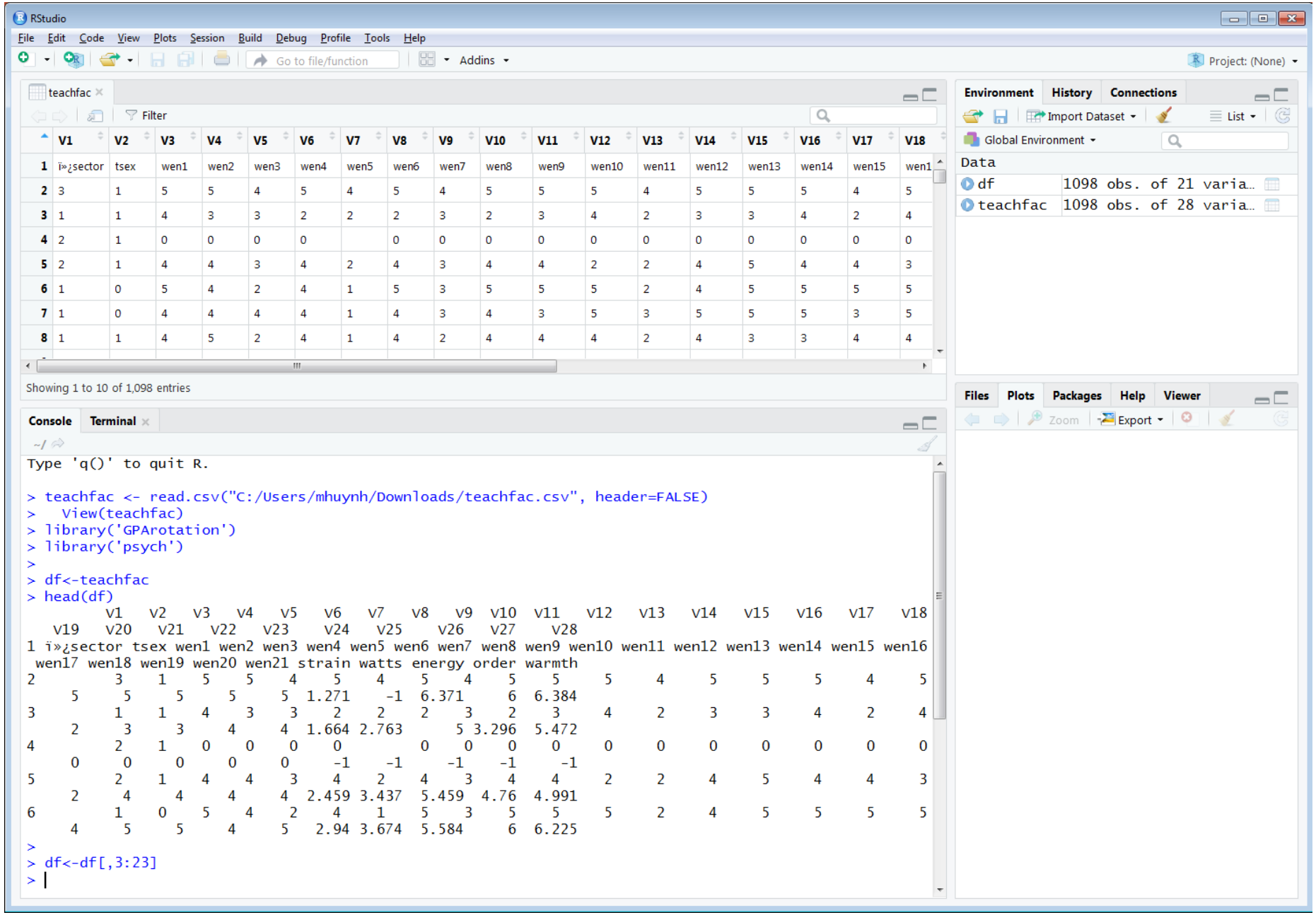
	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12	V13	V14	V15	V16	V17	V18	V19	V20	V21	V22	V23	V24	V25	V26	V27	V28
1	ï»¿sector	tsex	wen1	wen2	wen3	wen4	wen5	wen6	wen7	wen8	wen9	wen10	wen11	wen12	wen13	wen14	wen15	wen16	wen17	wen18	wen19	wen20	wen21	strain	watts	energy	order	warmth
2	3	1	5	5	4	5	4	5	4	5	5	5	4	5	5	5	4	5	5	5	5	5	5	1.271	-1	6.371	6	6.384
3	1	1	4	3	3	2	2	2	3	2	3	4	2	3	3	4	2	4	2	3	3	4	4	1.664	2.763	5	3.296	5.472
4	2	1	0	0	0	0		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-1	-1	-1	-1	-1
5	2	1	4	4	3	4	2	4	3	4	4	2	2	4	5	4	4	3	2	4	4	4	4	2.459	3.437	5.459	4.76	4.991
6	1	0	5	4	2	4	1	5	3	5	5	5	2	4	5	5	5	5	4	5	5	4	5	2.94	3.674	5.584	6	6.225
7	1	0	4	4	4	4	1	4	3	4	3	5	3	5	5	5	3	5	3	3	3	4	5	2.155	3.437	5.225	4.779	6.289
8	1	1	4	5	2	4	1	4	2	4	4	4	2	4	3	3	4	4	2	4	4	4	4	1.669	3	6.618	3	6.448
9	2	1	4	4	2	5	4	5	2	5	5	4	2	4	5	4	4	4	2	4	4	5	4	2.271	4.437	5.682	4	4.92
10	2	1	4	3	2	4	2	4	1	5	4	5	4	4	4	4	4	4	3	4	4	4	5	2.155	3.237	6.809	3.416	5.47
11	1	1	4	4	3	5	2	3	3	4	3	4	3	3	3	4	3	4	4	4	4	4	4	4	3.002	5.022	6.517	6.936
12	1	1	4	4	3	4	3	4	4	3	3	4	4	3	5	3	3	3	4	4	3	4	3	2.607	3.549	4.88	5.659	5.472

Note: For this exercise, we are only interested in the *wen* items (variable 3 to 23)

V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12	V13	V14	V15	V16	V17	V18	V19	V20	V21	V22	V23	V24	V25	V26	V27	V28
ï»¿sector	tsex	wen1	wen2	wen3	wen4	wen5	wen6	wen7	wen8	wen9	wen10	wen11	wen12	wen13	wen14	wen15	wen16	wen17	wen18	wen19	wen20	wen21	strain	watts	energy	order	warmth
3	1	5	5	4	5	4	5	4	5	5	5	4	5	5	5	4	5	5	5	5	5	5	1.271	-1	6.371	6	6.384
1	1	4	3	3	2	2	2	3	2	3	4	2	3	3	4	2	4	2	3	3	4	4	1.664	2.763	5	3.296	5.472
2	1	0	0	0	0		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-1	-1	-1	-1	-1
2	1	4	4	3	4	2	4	3	4	4	2	2	4	5	4	4	3	2	4	4	4	4	2.459	3.437	5.459	4.76	4.991
1	0	5	4	2	4	1	5	3	5	5	5	2	4	5	5	5	5	4	5	5	4	5	2.94	3.674	5.584	6	6.225

5 Redefine data frame for variables of interest only (3:23)

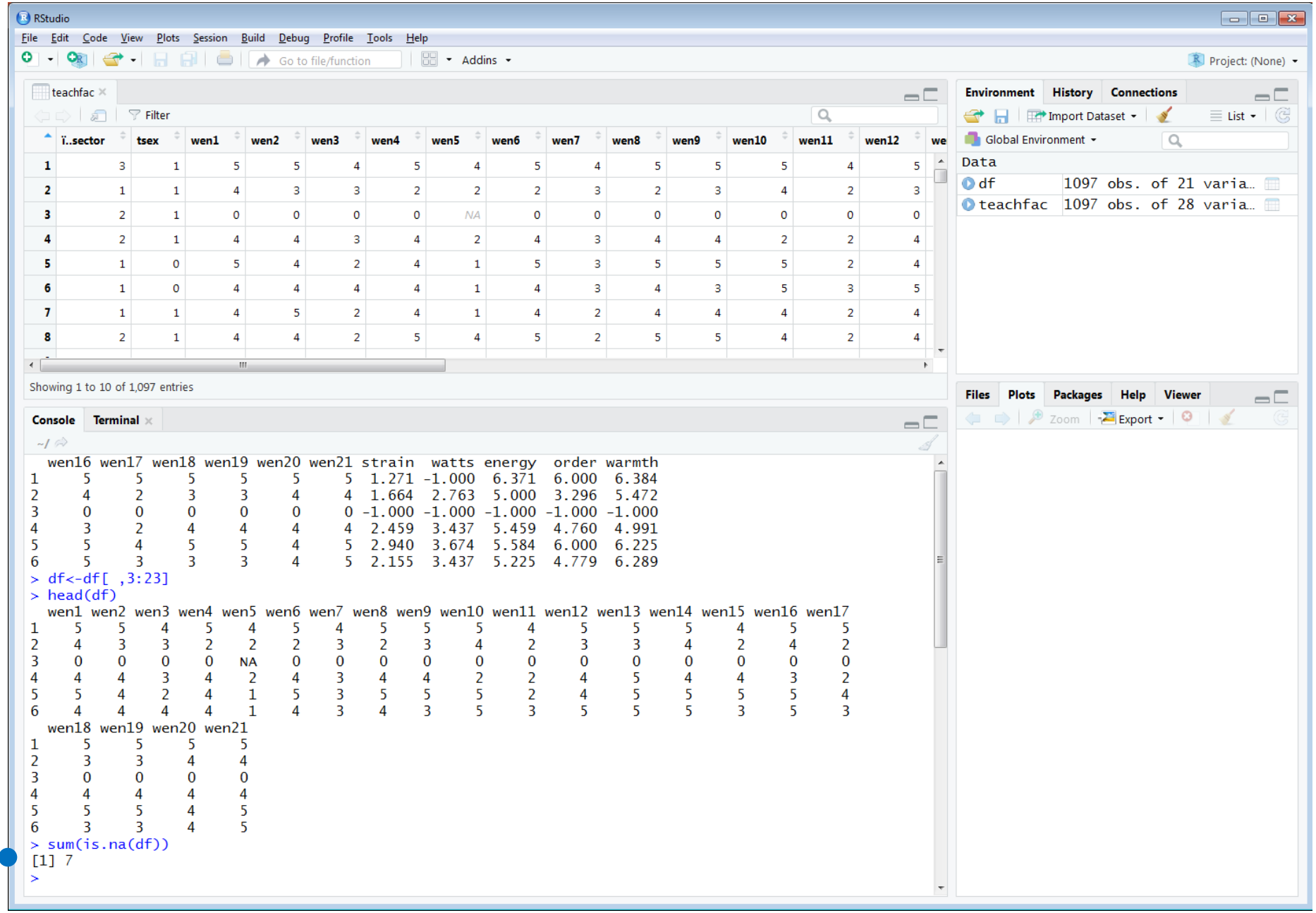
> df<-df[,3:23]



6 Determine number of missing cases

```
> sum(is.na(df))
```

Here we can see that it's seven

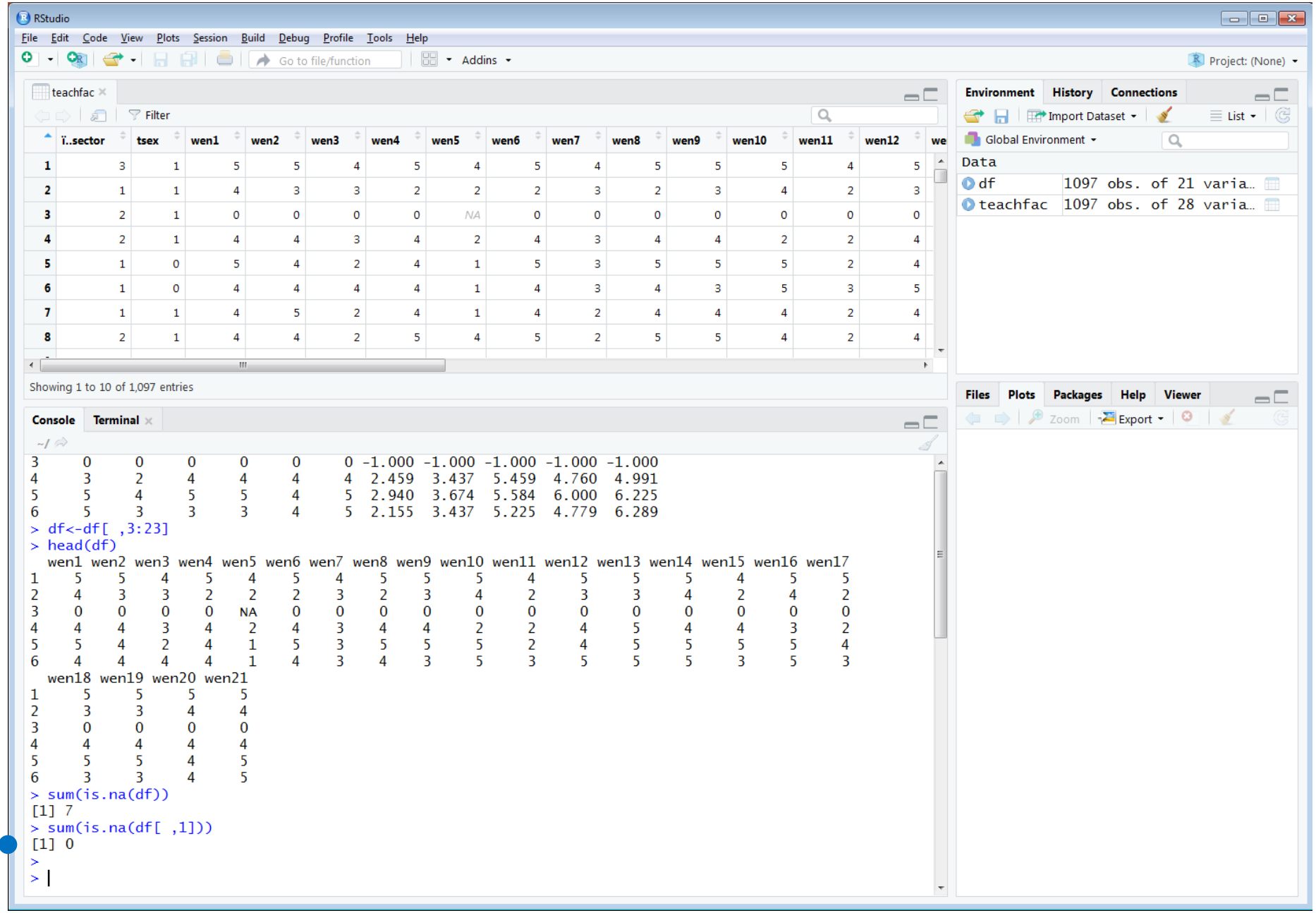


7

Check how many missing cases there are in Column 1

> sum(is.na(df[,1]))

Here we can see that it's zero

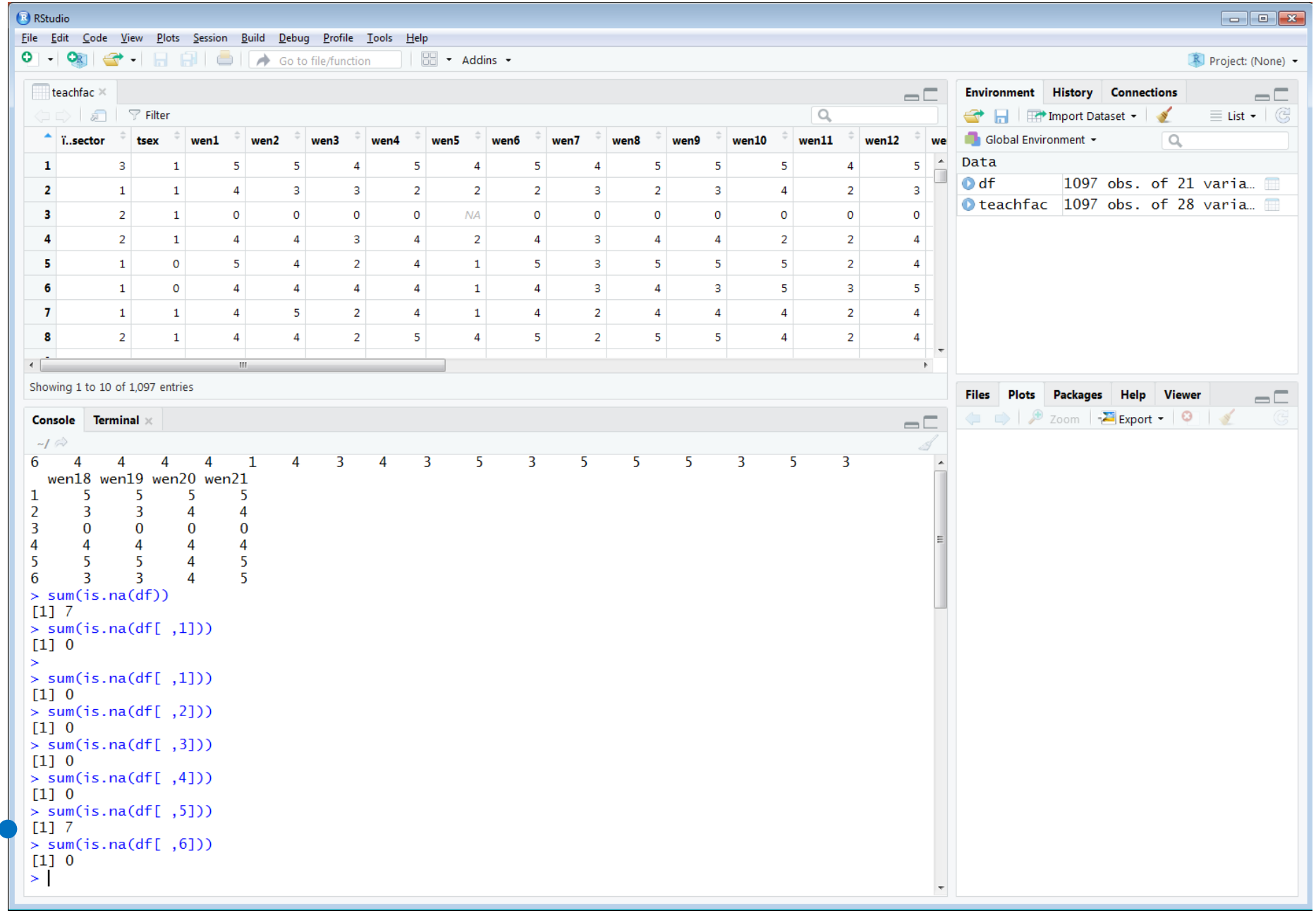


8

Repeat for all 21 columns to find columns with missing

```
>       sum(is.na(df[ ,1]))
>       sum(is.na(df[ ,2]))
>       sum(is.na(df[ ,3]))
>       sum(is.na(df[ ,4]))
>       sum(is.na(df[ ,5]))
>                 …
>       sum(is.na(df[ ,21]))
```

Here we can stop at column 5 because all seven were found in the same column

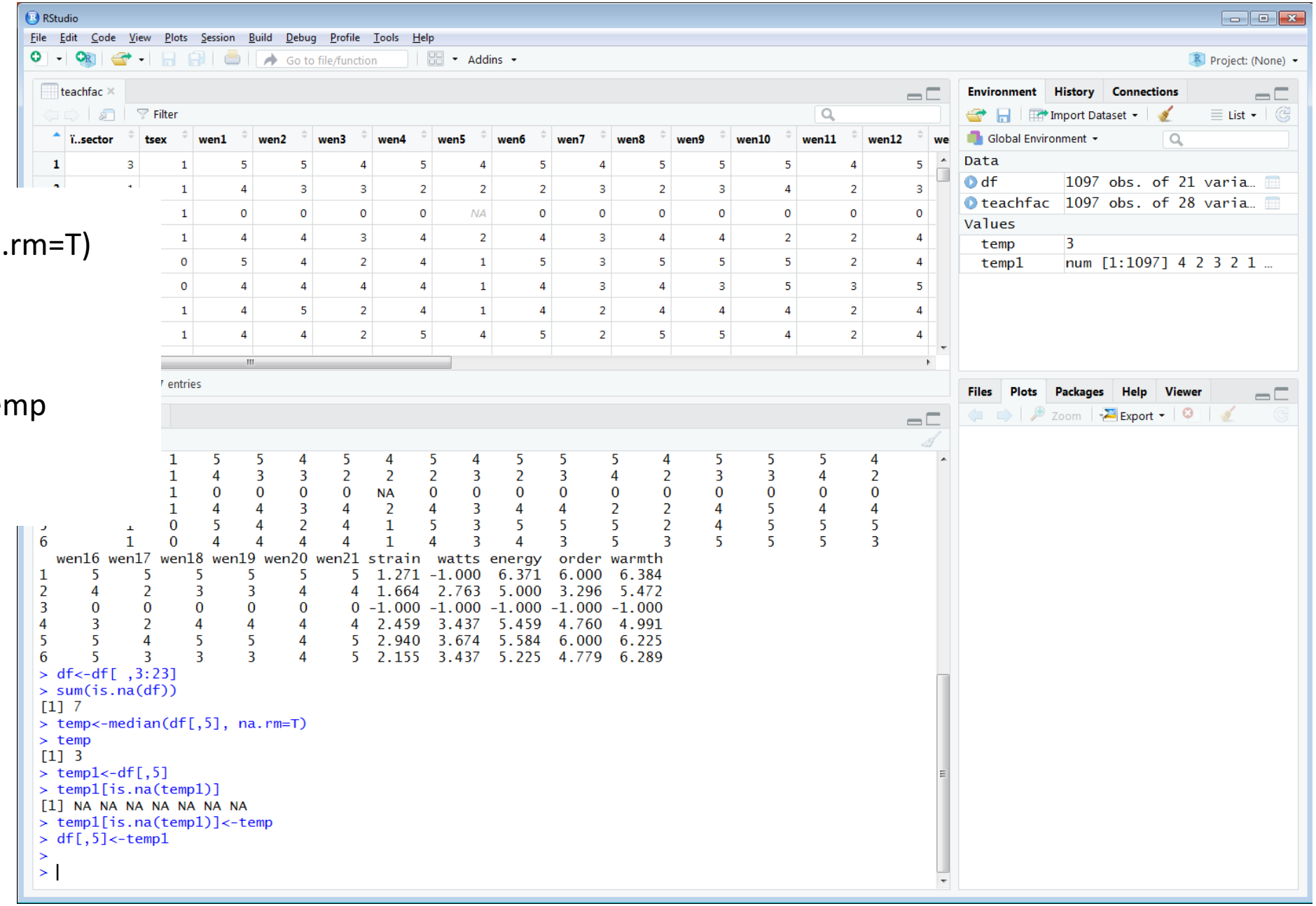


Bonus task (for later): write a code that loops through all columns

9

Replace the missing values from column 5 with the median

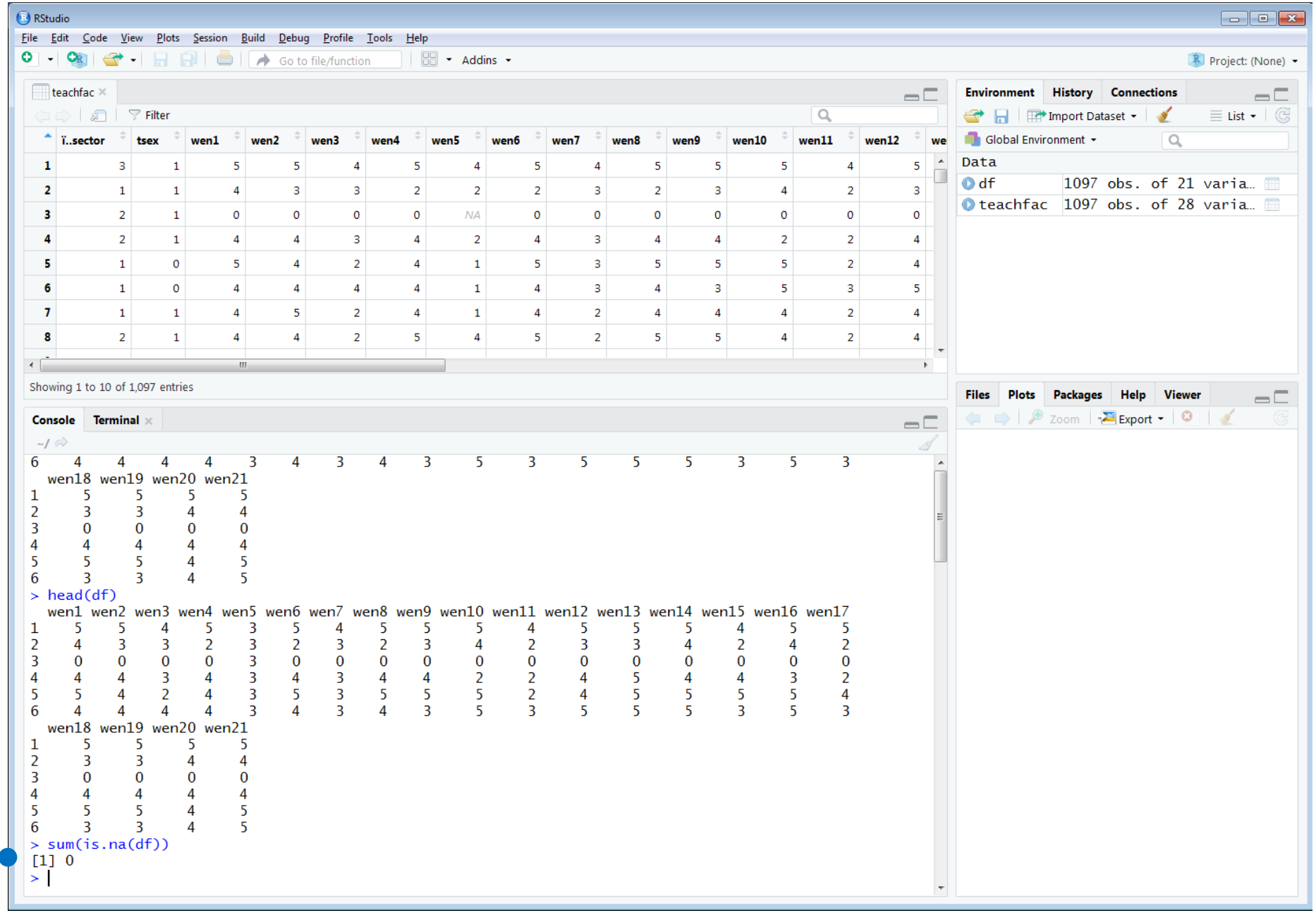
```
> temp<-median(df[,5], na.rm=T)
> temp
> temp1<-df[,5]
> temp1[is.na(temp1)]
> temp1[is.na(temp1)]<-temp
> df[,5]<-temp1
```



10 Recheck the number of missing cases (should be zero now)

```
>     sum(is.na(df))
```

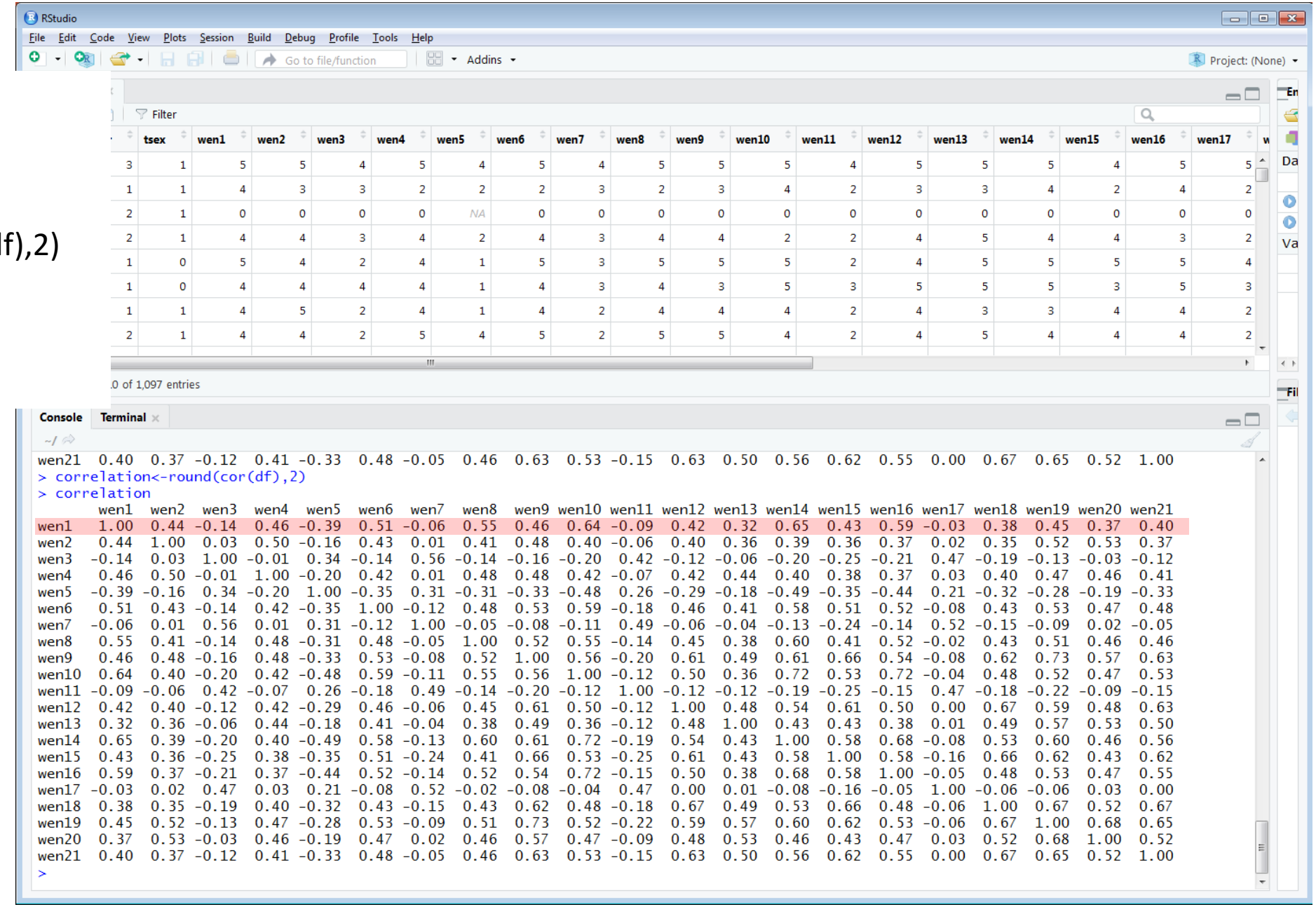
Here we can see that it's zero after replacing with the median



11 Check the correlation matrix

```
> correlation<-round(cor(df),2)
> correlation
```

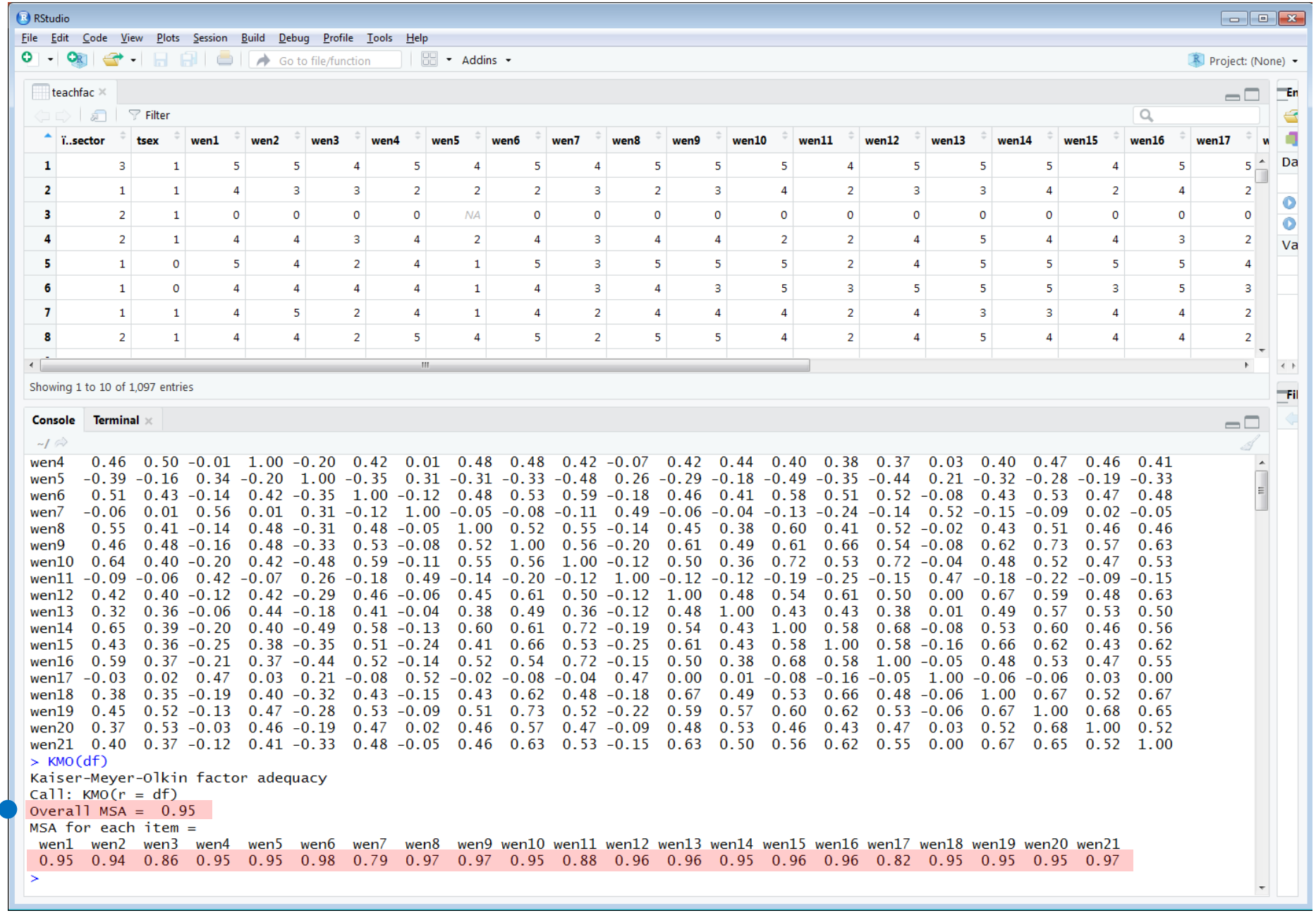
Do all variables have **at least one** correlation with another variable that is larger than .30?



12 Check sampling accuracy with KMO

> kmo(df)

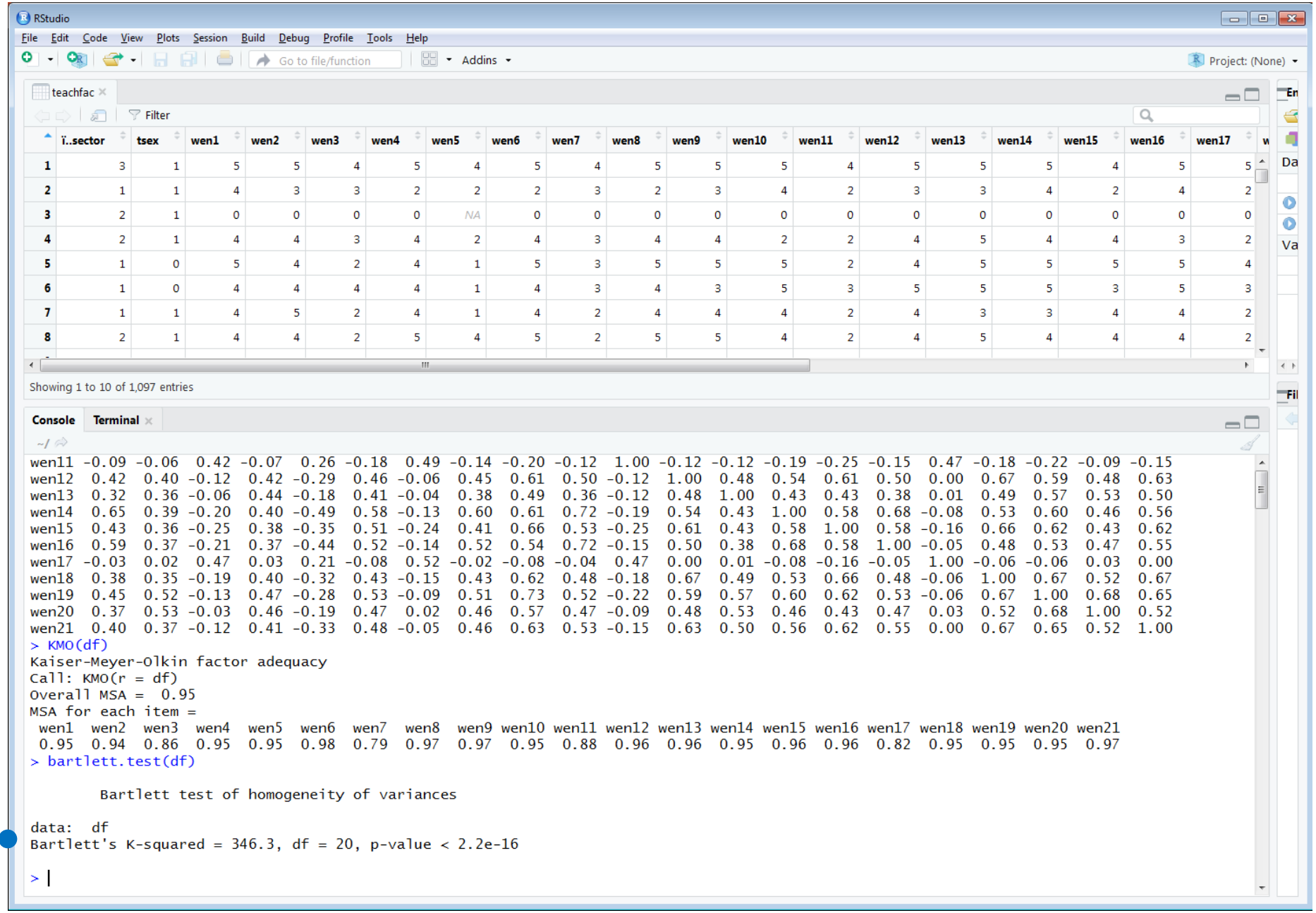
The overall MSA is larger than 0.60



13 Compare correlation matrix to identity matrix

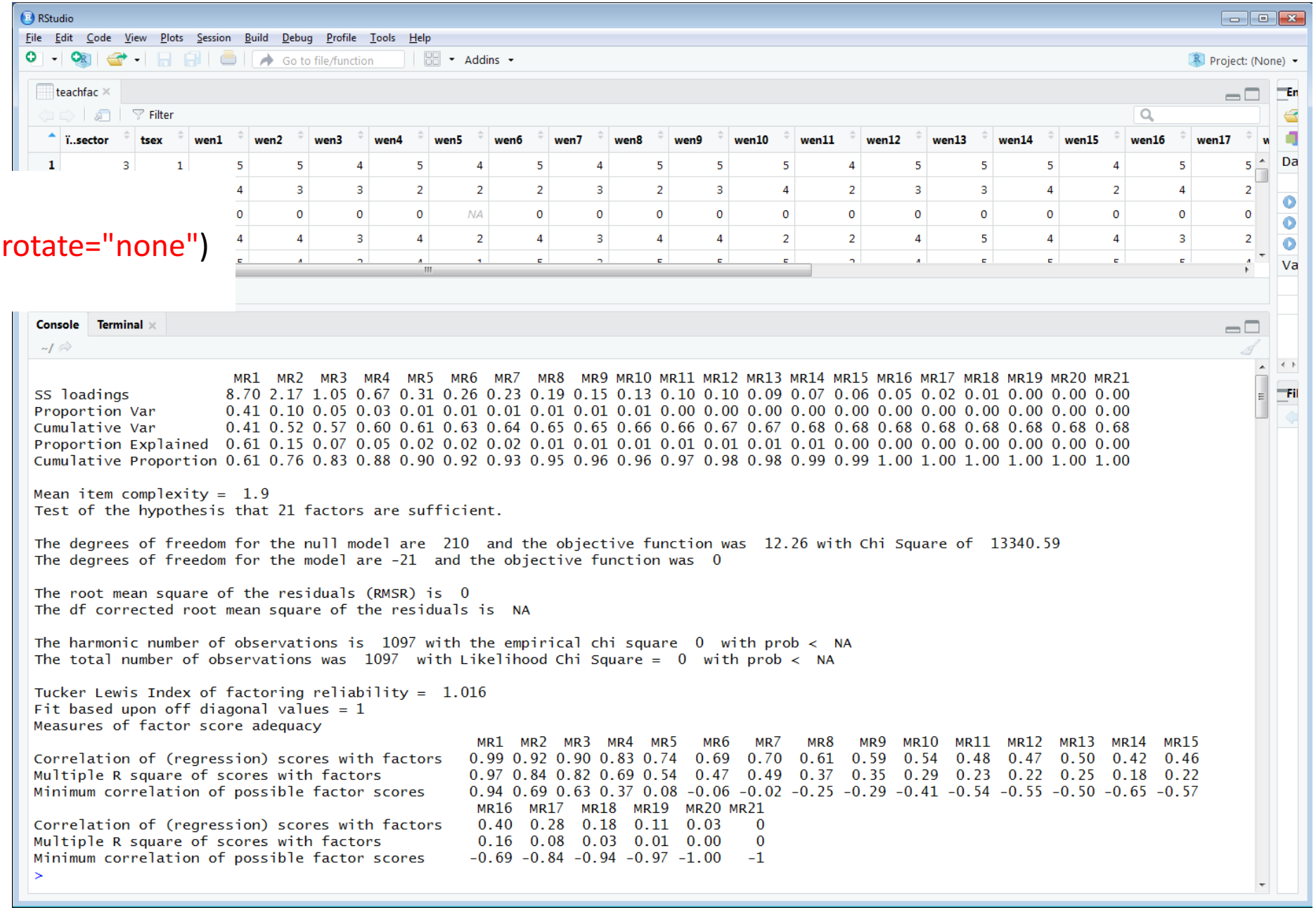
> bartlett.test(df)

Bartlett's test is significant so FA is suitable



14 Obtain the initial (un-rotated) factor loadings

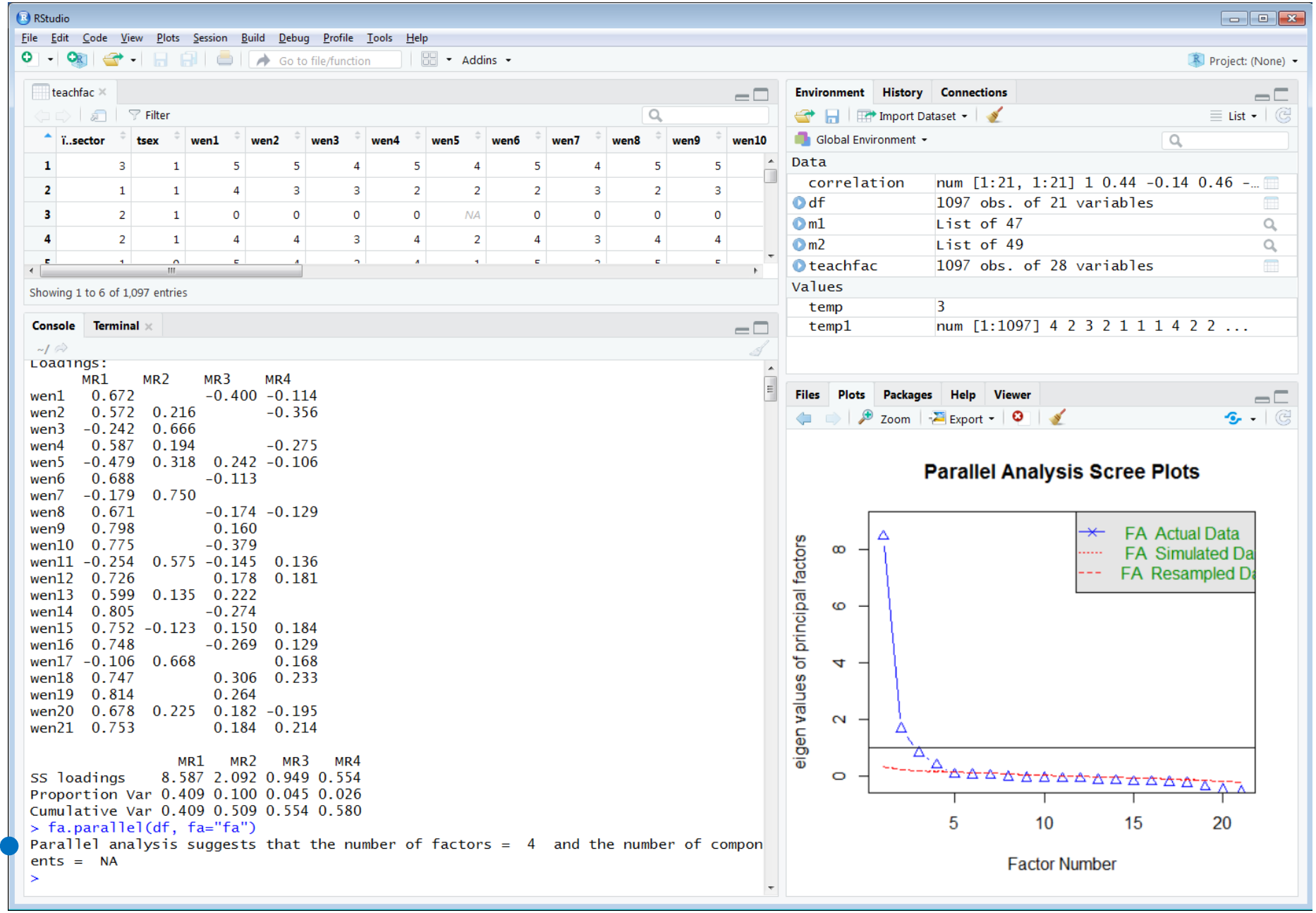
```
> m1<-fa(df, nfactors = 21, rotate="none")
```




```
                        MR1  MR2  MR3  MR4  MR5  MR6  MR7  MR8  MR9 MR10 MR11 MR12 MR13 MR14 MR15 MR16 MR17 MR18 MR19 MR20 MR21
SS loadings            8.70 2.17 1.05 0.67 0.31 0.26 0.23 0.19 0.15 0.13 0.10 0.10 0.09 0.07 0.06 0.05 0.02 0.01 0.00 0.00 0.00
Proportion Var         0.41 0.10 0.05 0.03 0.01 0.01 0.01 0.01 0.01 0.01 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
Cumulative Var         0.41 0.52 0.57 0.60 0.61 0.63 0.64 0.65 0.65 0.66 0.66 0.67 0.67 0.68 0.68 0.68 0.68 0.68 0.68 0.68 0.68
Proportion Explained   0.61 0.15 0.07 0.05 0.02 0.02 0.02 0.01 0.01 0.01 0.01 0.01 0.01 0.01 0.00 0.00 0.00 0.00 0.00 0.00 0.00
Cumulative Proportion  0.61 0.76 0.83 0.88 0.90 0.92 0.93 0.95 0.96 0.96 0.97 0.98 0.98 0.99 0.99 1.00 1.00 1.00 1.00 1.00 1.00

Mean item complexity =  1.9
Test of the hypothesis that 21 factors are sufficient.

The degrees of freedom for the null model are  210  and the objective function was  12.26 with Chi Square of  13340.59
The degrees of freedom for the model are -21  and the objective function was  0

The root mean square of the residuals (RMSR) is  0
The df corrected root mean square of the residuals is  NA

The harmonic number of observations is  1097 with the empirical chi square  0  with prob <  NA
The total number of observations was  1097  with Likelihood Chi Square =  0  with prob <  NA

Tucker Lewis Index of factoring reliability =  1.016
Fit based upon off diagonal values = 1
Measures of factor score adequacy
                                                 MR1  MR2  MR3  MR4  MR5   MR6   MR7   MR8   MR9  MR10  MR11  MR12  MR13  MR14  MR15
Correlation of (regression) scores with factors 0.99 0.92 0.90 0.83 0.74  0.69  0.70  0.61  0.59  0.54  0.48  0.47  0.50  0.42  0.46
Multiple R square of scores with factors        0.97 0.84 0.82 0.69 0.54  0.47  0.49  0.37  0.35  0.29  0.23  0.22  0.25  0.18  0.22
Minimum correlation of possible factor scores   0.94 0.69 0.63 0.37 0.08 -0.06 -0.02 -0.25 -0.29 -0.41 -0.54 -0.55 -0.50 -0.65 -0.57
                                                MR16  MR17  MR18  MR19  MR20 MR21
Correlation of (regression) scores with factors 0.40  0.28  0.18  0.11  0.03    0
Multiple R square of scores with factors        0.16  0.08  0.03  0.01  0.00    0
Minimum correlation of possible factor scores   -0.69 -0.84 -0.94 -0.97 -1.00   -1
>
```

15 Determine a suitable number of factors

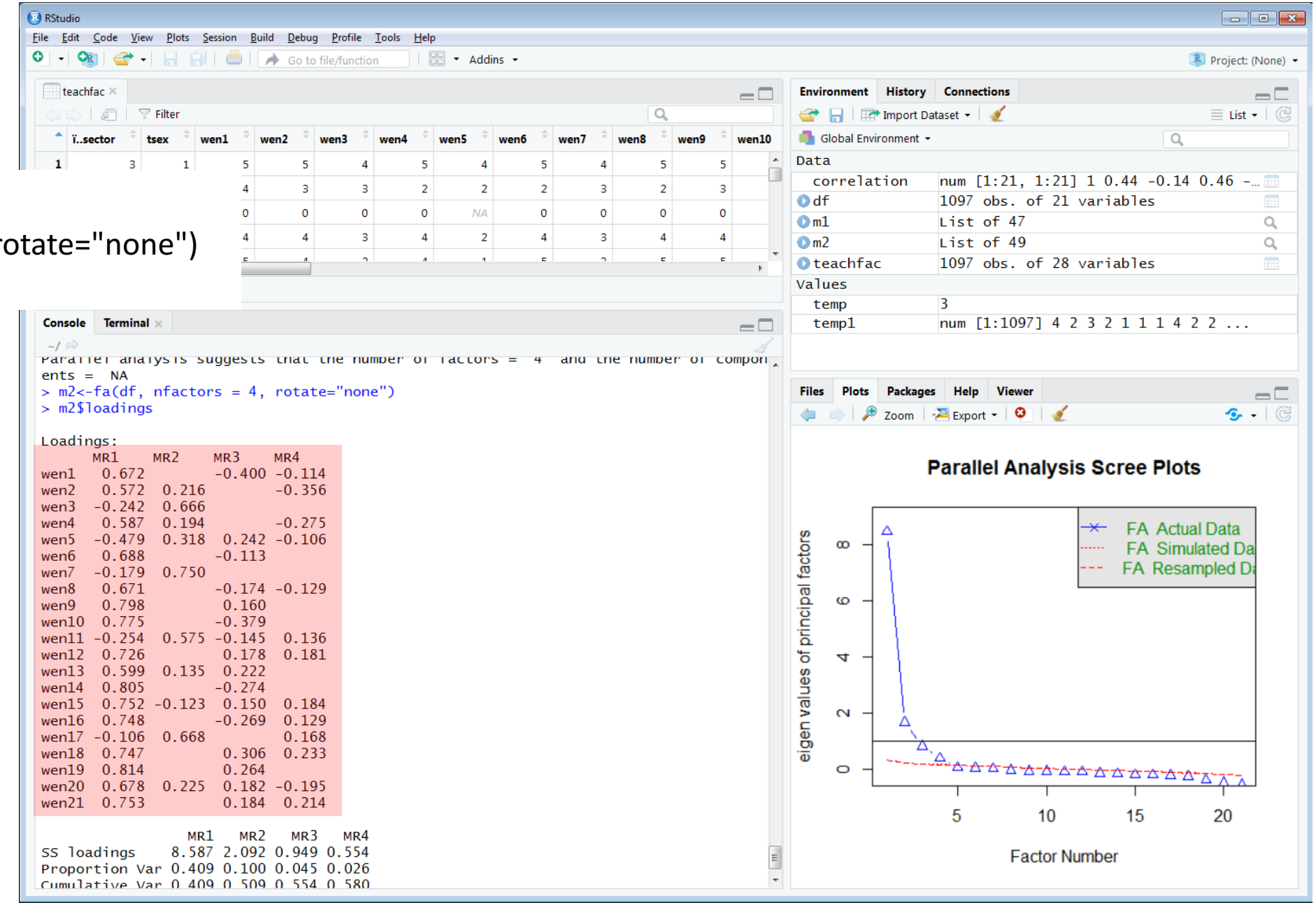
```
> fa.parallel(df, fa="fa")
```



16 Run a second model with 4 factors (still un-rotated)

```
> m2<-fa(df, nfactors = 4, rotate="none")
> m2$loadings
```

This is not a simple structure (where each variable loads highly onto one and only one factor) so rotation is required

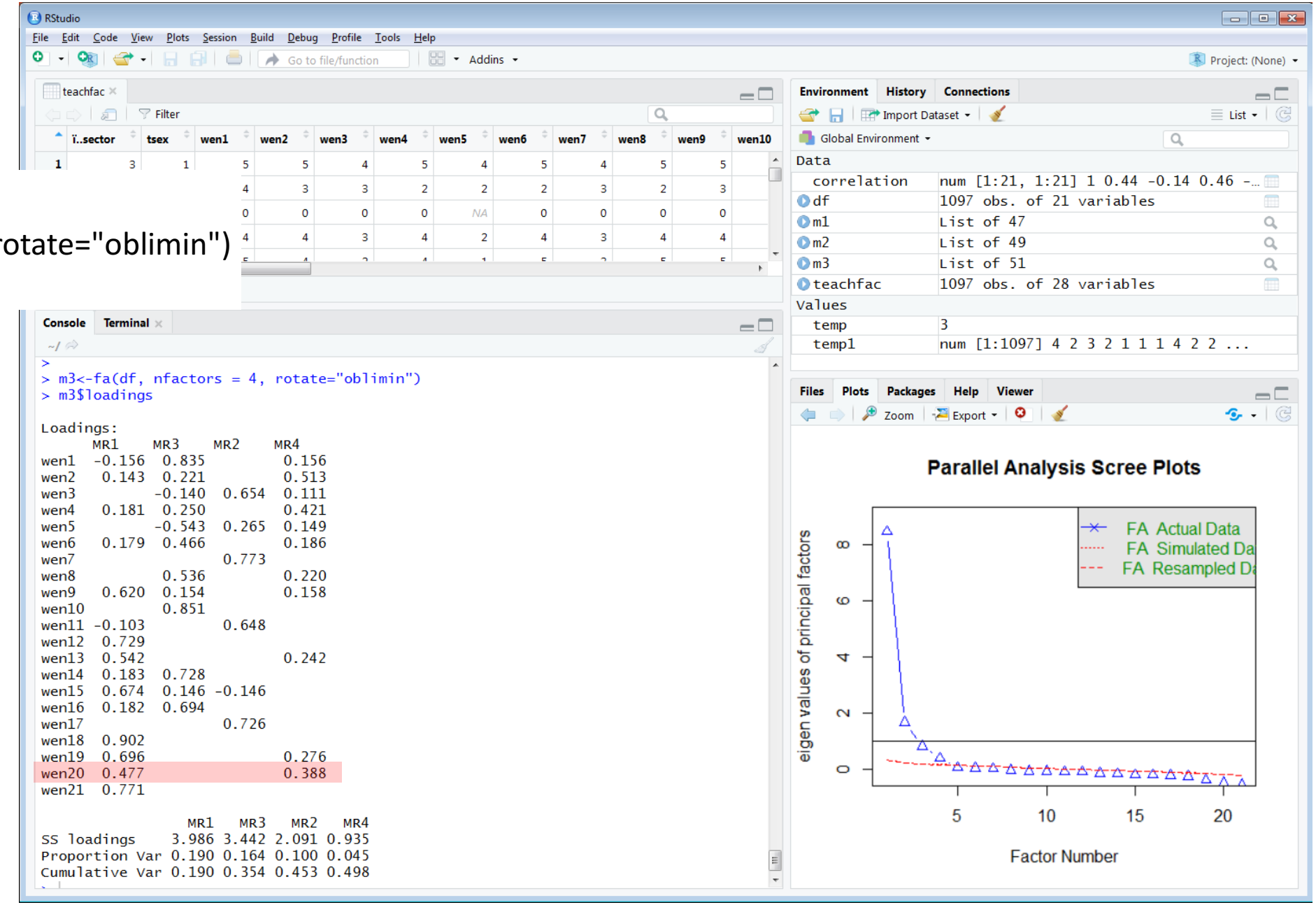


17 Run a third model using a rotation method (e.g. oblimin)

```
> m3<-fa(df, nfactors = 4, rotate="oblimin")
> m3$loadings
```

```
Loadings:
      MR1    MR3    MR2    MR4
wen1  -0.156  0.835         0.156
wen2   0.143  0.221         0.513
wen3         -0.140  0.654  0.111
wen4   0.181  0.250         0.421
wen5         -0.543  0.265  0.149
wen6   0.179  0.466         0.186
wen7                0.773
wen8          0.536         0.220
wen9   0.620  0.154         0.158
wen10         0.851
wen11 -0.103         0.648
wen12  0.729
wen13  0.542                0.242
wen14  0.183  0.728
wen15  0.674  0.146 -0.146
wen16  0.182  0.694
wen17               0.726
wen18  0.902
wen19  0.696                0.276
wen20  0.477                0.388
wen21  0.771

                MR1   MR3   MR2   MR4
SS loadings    3.986 3.442 2.091 0.935
Proportion Var 0.190 0.164 0.100 0.045
Cumulative Var 0.190 0.354 0.453 0.498
```

Item 20 is still loading highly across multiple factors (we should remove this item)



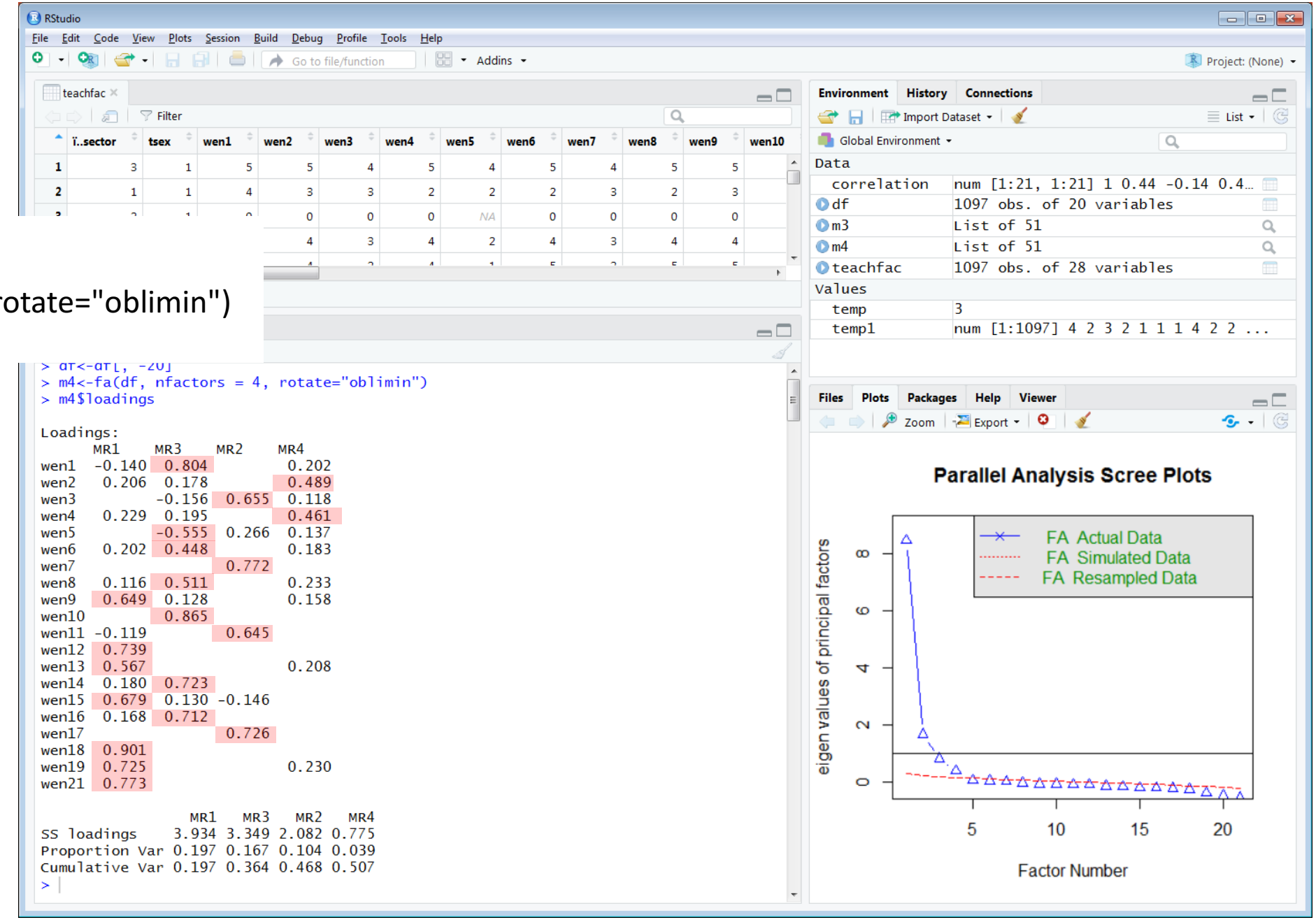
18 Remove item 20 and run a forth model

> df<-df[, -20]

> m4<-fa(df, nfactors = 4, rotate="oblimin")

> m4$loadings

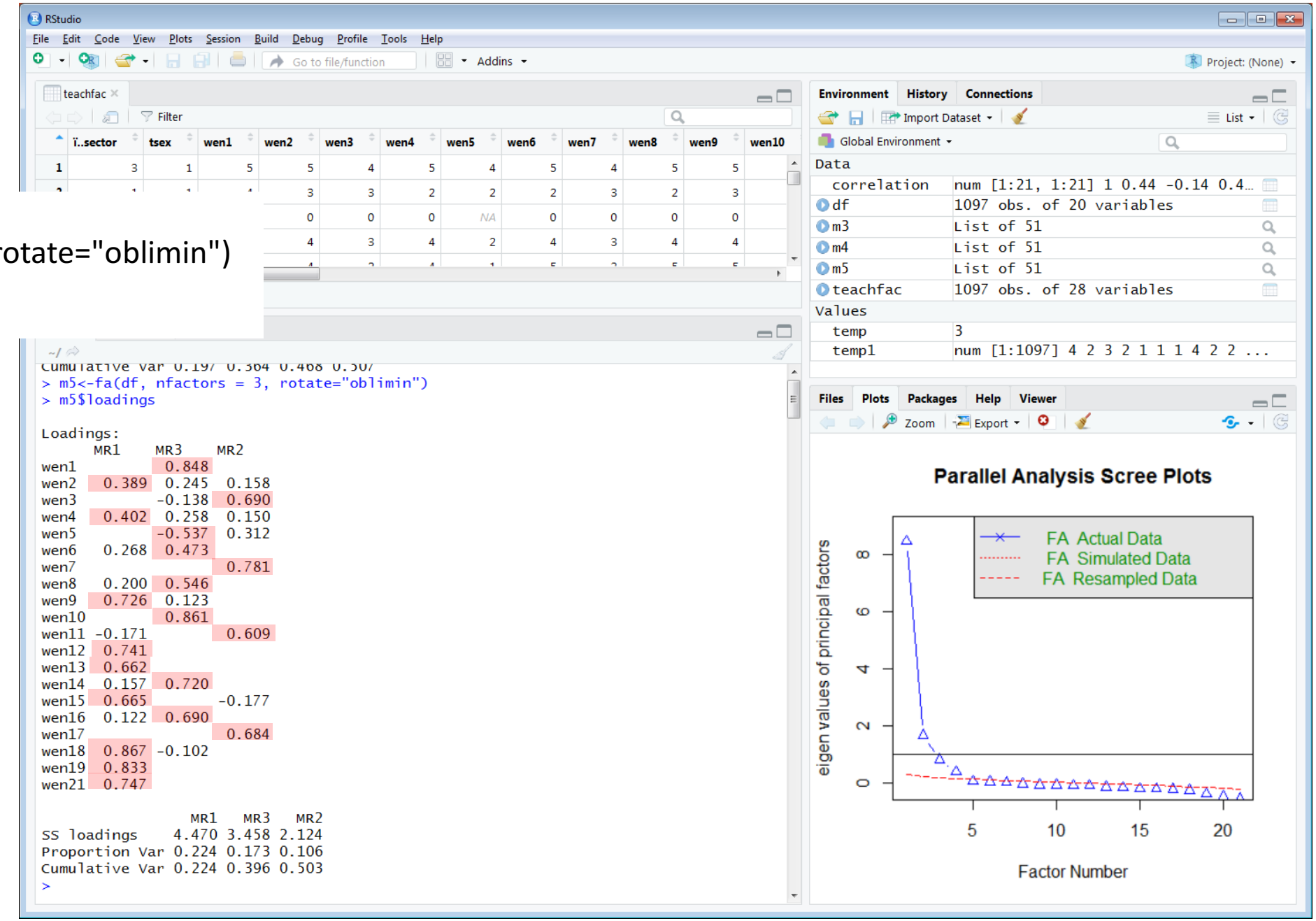
Here factor 4 only has two items loading highly onto it. We need to decide whether or not to remove it (for this example we will remove)



19 Remove item 20 and run a forth model

```
> m5<-fa(df, nfactors = 3, rotate="oblimin")
> m5$loadings
```

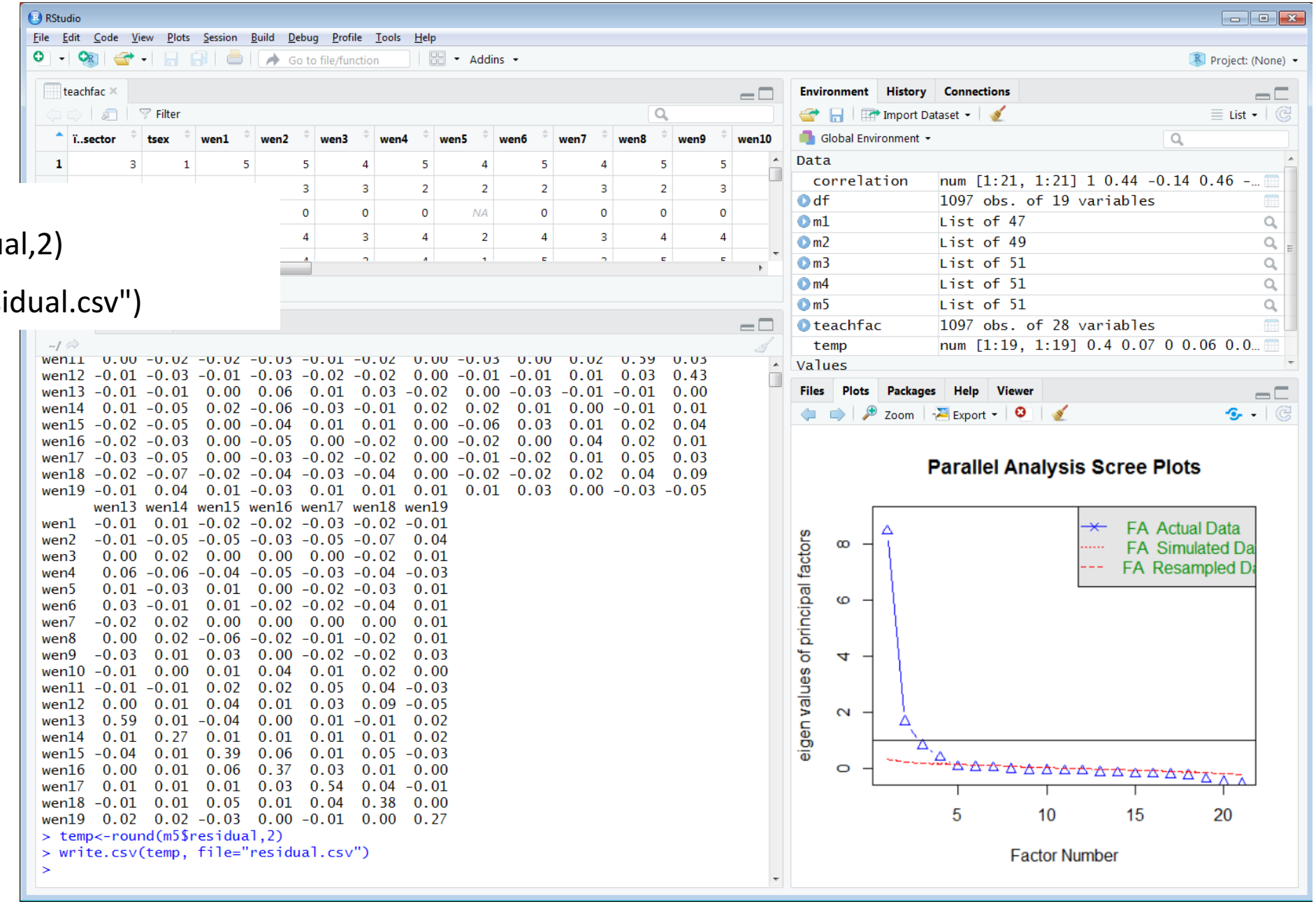
Much better:




```
> m5<-fa(df, nfactors = 3, rotate="oblimin")
> m5$loadings

Loadings:
      MR1    MR3    MR2
wen1         0.848
wen2   0.389 0.245  0.158
wen3        -0.138  0.690
wen4   0.402 0.258  0.150
wen5        -0.537  0.312
wen6   0.268 0.473
wen7                0.781
wen8   0.200 0.546
wen9   0.726 0.123
wen10        0.861
wen11 -0.171        0.609
wen12  0.741
wen13  0.662
wen14  0.157 0.720
wen15  0.665       -0.177
wen16  0.122 0.690
wen17               0.684
wen18  0.867 -0.102
wen19  0.833
wen21  0.747

                 MR1   MR3   MR2
SS loadings    4.470 3.458 2.124
Proportion Var 0.224 0.173 0.106
Cumulative Var 0.224 0.396 0.503
>
```

20 Export the residual matrix as a csv file

```
> temp<-round(m5$residual,2)
> write.csv(temp, file="residual.csv")
```



21 Check which variables have high residuals

=COUNTIF(B2:U2,">.05")

Consider removing item 4

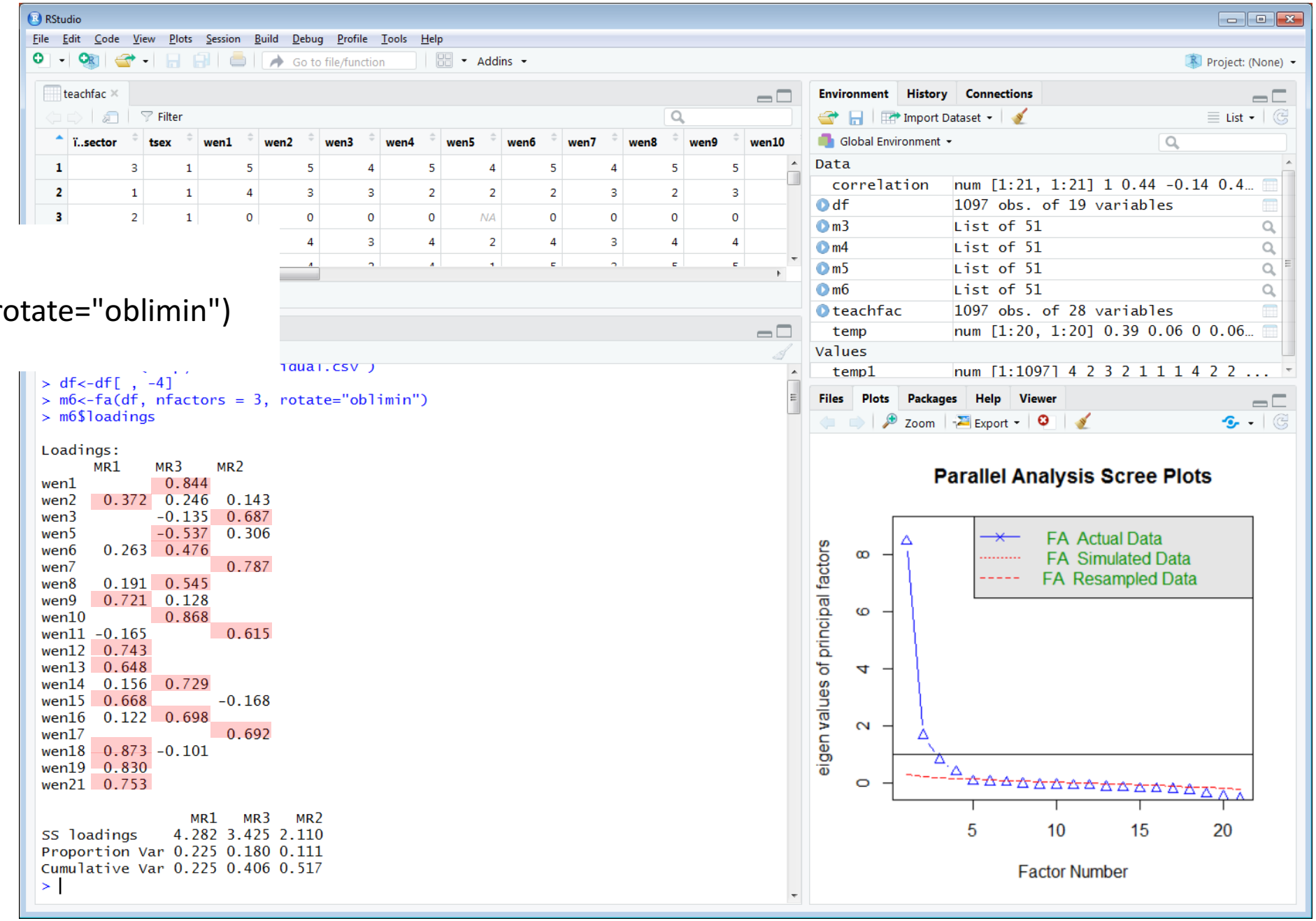
	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	W	X
1		wen1	wen2	wen3	wen4	wen5	wen6	wen7	wen8	wen9	wen10	wen11	wen12	wen13	wen14	wen15	wen16	wen17	wen18	wen19	wen21		
2	wen1	0.39	0.06	0	0.06	0.02	0	-0.01	0.03	-0.01	-0.03	0	0	-0.01	0.01	-0.01	-0.02	-0.03	0	0	-0.03	3	16%
3	wen2	0.06	0.66	0.03	0.14	0.05	0.05	-0.03	0.03	0.02	-0.03	-0.03	-0.02	0.01	-0.05	-0.04	-0.04	-0.05	-0.06	0.06	-0.06	4	21%
4	wen3	0	0.03	0.49	0.01	0.01	0.02	0.01	-0.03	-0.01	-0.01	-0.02	-0.01	0	0.02	0	0	0	-0.02	0.01	0	1	5%
5	wen4	0.06	0.14	0.01	0.63	0.03	0.02	-0.02	0.08	0.01	-0.03	-0.03	-0.03	0.07	-0.06	-0.04	-0.06	-0.03	-0.04	-0.01	-0.04	5	26%
6	wen5	0.02	0.05	0.01	0.03	0.62	0.01	0	0.03	0	-0.02	-0.01	-0.02	0.01	-0.03	0.01	-0.01	-0.03	-0.03	0.02	-0.04	1	5%
7	wen6	0	0.05	0.02	0.02	0.01	0.51	-0.01	0	0	0.01	-0.02	-0.02	0.03	-0.01	0.01	-0.02	-0.02	-0.04	0.01	-0.01	1	5%
8	wen7	-0.01	-0.03	0.01	-0.02	0	-0.01	0.39	0.01	0.03	0	0	0	-0.02	0.02	-0.01	0	0	-0.01	0	0.02	1	5%
9	wen8	0.03	0.03	-0.03	0.08	0.03	0	0.01	0.52	0.01	-0.03	-0.03	-0.01	0.01	0.02	-0.05	-0.02	-0.01	-0.01	0.01	-0.02	2	11%
10	wen9	-0.01	0.02	-0.01	0.01	0	0	0.03	0.01	0.33	0	-0.01	-0.01	-0.03	0	0.03	-0.01	-0.02	-0.03	0.04	-0.01	1	5%
11	wen10	-0.03	-0.03	-0.01	-0.03	-0.02	0.01	0	-0.03	0	0.26	0.03	0.01	-0.02	0	0.01	0.05	0.02	0.02	-0.01	0.02	1	5%
12	wen11	0	-0.03	-0.02	-0.03	-0.01	-0.02	0	-0.03	-0.01	0.03	0.59	0.03	-0.02	-0.01	0.02	0.02	0.05	0.04	-0.03	0	1	5%
13	wen12	0	-0.02	-0.01	-0.03	-0.02	-0.02	0	-0.01	-0.01	0.01	0.03	0.41	-0.01	0.01	0.03	0.01	0.02	0.06	-0.06	0.03	2	11%
14	wen13	-0.01	0.01	0	0.07	0.01	0.03	-0.02	0.01	-0.03	-0.02	-0.02	-0.01	0.59	0.01	-0.05	-0.01	0	-0.02	0.03	0	2	11%
15	wen14	0.01	-0.05	0.02	-0.06	-0.03	-0.01	0.02	0.02	0	0	-0.01	0.01	0.01	0.28	0.01	0.01	0.01	0.01	0.02	0	1	5%
16	wen15	-0.01	-0.04	0	-0.04	0.01	0.01	-0.01	-0.05	0.03	0.01	0.02	0.03	-0.05	0.01	0.38	0.05	0.01	0.03	-0.03	0.02	1	5%
17	wen16	-0.02	-0.04	0	-0.06	-0.01	-0.02	0	-0.02	-0.01	0.05	0.02	0.01	-0.01	0.01	0.05	0.38	0.03	0.01	-0.01	0.04	1	5%
18	wen17	-0.03	-0.05	0	-0.03	-0.03	-0.02	0	-0.01	-0.02	0.02	0.05	0.02	0	0.01	0.01	0.03	0.54	0.03	-0.01	0.03	1	5%
19	wen18	0	-0.06	-0.02	-0.04	-0.03	-0.04	-0.01	-0.01	-0.03	0.02	0.04	0.06	-0.02	0.01	0.03	0.01	0.03	0.34	-0.01	0.04	2	11%
20	wen19	0	0.06	0.01	-0.01	0.02	0.01	0	0.01	0.04	-0.01	-0.03	-0.06	0.03	0.02	-0.03	-0.01	-0.01	-0.01	0.28	-0.02	2	11%
21	wen21	-0.03	-0.06	0	-0.04	-0.04	-0.01	0.02	-0.02	-0.01	0.02	0	0.03	0	0	0.02	0.04	0.03	0.04	-0.02	0.38	1	5%

22 Remove item 4 and run a sixth model

```
> df<-df[ , -4]
> m6<-fa(df, nfactors = 3, rotate="oblimin")
> m6$loadings
```

Factor loadings are still good:

```
> df<-df[ , -4]
> m6<-fa(df, nfactors = 3, rotate="oblimin")
> m6$loadings

Loadings:
      MR1    MR3    MR2
wen1         0.844
wen2  0.372  0.246  0.143
wen3        -0.135  0.687
wen5        -0.537  0.306
wen6  0.263  0.476
wen7                0.787
wen8  0.191  0.545
wen9  0.721  0.128
wen10        0.868
wen11 -0.165        0.615
wen12 0.743
wen13 0.648
wen14 0.156  0.729
wen15 0.668        -0.168
wen16 0.122  0.698
wen17               0.692
wen18 0.873 -0.101
wen19 0.830
wen21 0.753

                MR1   MR3   MR2
SS loadings   4.282 3.425 2.110
Proportion Var 0.225 0.180 0.111
Cumulative Var 0.225 0.406 0.517
>
```



23 Export the residual matrix as a csv file for the new model

=COUNTIF(B2:U2,">.05")

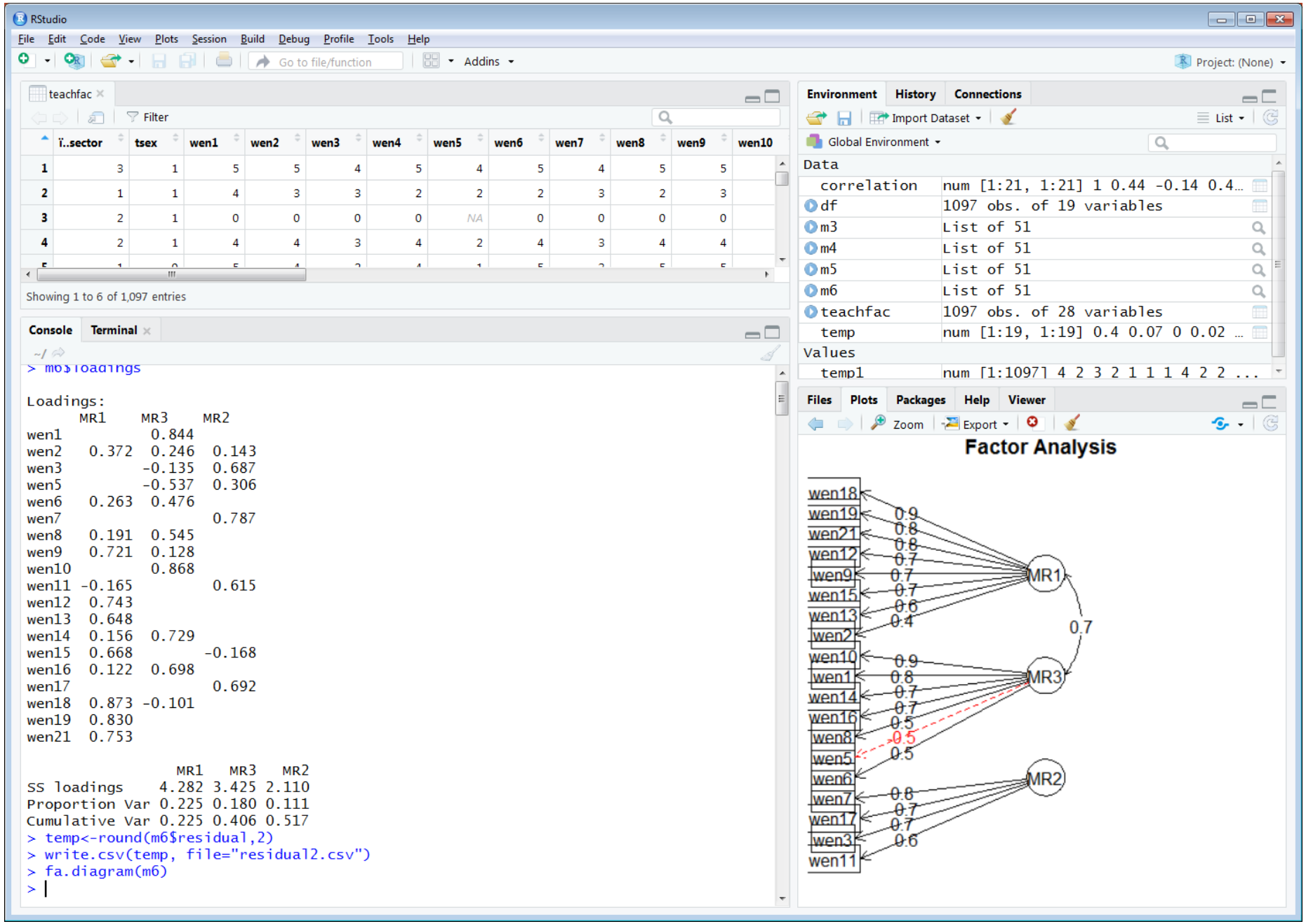
Much better:

```
> temp<-round(m6$residual,2)
> write.csv(temp, file="residual2.csv")
```

		D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W
		wen3	wen5	wen6	wen7	wen8	wen9	wen10	wen11	wen12	wen13	wen14	wen15	wen16	wen17	wen18	wen19	wen21			
		0	0.02	0.01	0	0.04	-0.01	-0.02	0	0	0	0.01	-0.01	-0.02	-0.02	0	0	-0.03		2	0.105263
		0.04	0.05	0.06	-0.02	0.04	0.03	-0.02	-0.02	-0.01	0.02	-0.05	-0.03	-0.03	-0.04	-0.05	0.07	-0.05		4	0.210526
		0.49	0.02	0.02	0.01	-0.02	0	-0.01	-0.02	-0.02	0	0.01	0	-0.01	-0.01	-0.02	0.01	0		1	0.052632
		0.02	0.62	0.01	0.01	0.03	0	-0.02	-0.01	-0.02	0.02	-0.03	0.01	-0.01	-0.03	-0.03	0.03	-0.04		1	0.052632
		0.02	0.01	0.52	-0.01	0.01	0	0.01	-0.02	-0.02	0.04	-0.01	0.01	-0.02	-0.02	-0.04	0.01	-0.01		2	0.105263
		0.01	0.01	-0.01	0.39	0.01	0.03	0	0	-0.01	-0.02	0.01	-0.01	-0.01	-0.01	-0.01	0	0.02		1	0.052632
		-0.02	0.03	0.01	0.01	0.53	0.02	-0.03	-0.03	-0.01	0.02	0.02	-0.05	-0.02	-0.01	-0.01	0.02	-0.02		1	0.052632
9	wen9	-0.01	0.03	0	0	0	0.03	0.02	0.33	0	-0.01	-0.01	-0.02	0	0.03	-0.01	-0.03	-0.04	0.04	-0.02		1	0.052632
10	wen10	-0.02	-0.02	-0.01	-0.02	0.01	0	-0.03	0	0.26	0.02	0	-0.02	-0.01	0.01	0.04	0.01	0.02	-0.01	0.02		1	0.052632
11	wen11	0	-0.02	-0.02	-0.01	-0.02	0	-0.03	-0.01	0.02	0.59	0.03	-0.01	-0.01	0.02	0.02	0.04	0.03	-0.03	0		1	0.052632
12	wen12	0	-0.01	-0.02	-0.02	-0.02	-0.01	-0.01	-0.01	0	0.03	0.41	0	0	0.02	0	0.02	0.06	-0.06	0.02		2	0.105263
13	wen13	0	0.02	0	0.02	0.04	-0.02	0.02	-0.02	-0.02	-0.01	0	0.6	0.01	-0.04	-0.01	0	-0.02	0.04	0		1	0.052632
14	wen14	0.01	-0.05	0.01	-0.03	-0.01	0.01	0.02	0	-0.01	-0.01	0	0.01	0.27	0	0	0	0	0.01	0		1	0.052632
15	wen15	-0.01	-0.03	0	0.01	0.01	-0.01	-0.05	0.03	0.01	0.02	0.02	-0.04	0	0.38	0.05	0	0.03	-0.03	0.01		1	0.052632
16	wen16	-0.02	-0.03	-0.01	-0.01	-0.02	-0.01	-0.02	-0.01	0.04	0.02	0	-0.01	0	0.05	0.37	0.02	0	-0.02	0.03		1	0.052632
17	wen17	-0.02	-0.04	-0.01	-0.03	-0.02	-0.01	-0.01	-0.03	0.01	0.04	0.02	0	0	0	0.02	0.53	0.03	-0.02	0.02		1	0.052632
18	wen18	0	-0.05	-0.02	-0.03	-0.04	-0.01	-0.01	-0.04	0.02	0.03	0.06	-0.02	0	0.03	0	0.03	0.33	-0.01	0.04		2	0.105263
19	wen19	0	0.07	0.01	0.03	0.01	0	0.02	0.04	-0.01	-0.03	-0.06	0.04	0.01	-0.03	-0.02	-0.02	-0.01	0.28	-0.02		2	0.105263
20	wen21	-0.03	-0.05	0	-0.04	-0.01	0.02	-0.02	-0.02	0.02	0	0.02	0	0	0.01	0.03	0.02	0.04	-0.02	0.37		1	0.052632
21																							

24 Obtain a summary factor diagram to see which items load where

```
> fa.diagram(m6)
```



25 Recount the column numbers for the remaining variables

RStudio

File Edit Code View Plots Session Build Debug Profile Tools Help

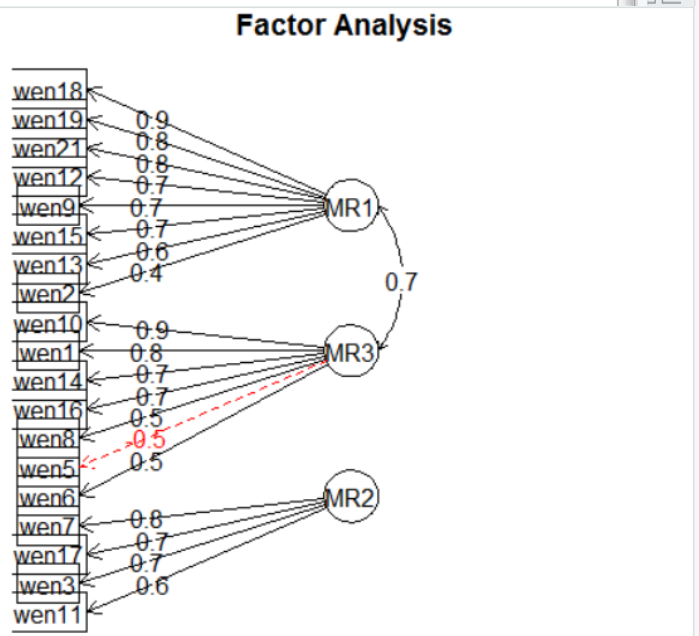
Go to file/function | Addins | Project: (None)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
	wen1	wen2	wen3	wen5	wen6	wen7	wen8	wen9	wen10	wen11	wen12	wen13	wen14	wen15	wen16	wen17	wen18	wen19	wen21
1	5	5	4	4	5	4	5	5	5	4	5	5	5	4	5	5	5	5	5
2	4	3	3	2	2	3	2	3	4	2	3	3	4	2	4	2	3	3	4
3	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	4	4	3	2	4	3	4	4	2	2	4	5	4	4	3	2	4	4	4
5	5	4	2	1	5	3	5	5	5	2	4	5	5	5	5	4	5	5	5
6	4	4	4	1	4	3	4	3	5	3	5	5	5	3	5	3	3	3	5

Showing 1 to 6 of 1,097 entries

Console Terminal

```
wen9  -0.0253105364 -0.0359215569  0.037087635 -0.0177528029
wen10  0.0133567073  0.0157788116 -0.011662946  0.0198706776
wen11  0.0441446138  0.0343384712 -0.033213983 -0.0004973291
wen12  0.0178133094  0.0560385897 -0.059669048  0.0188425009
wen13  0.0034911709 -0.0153449022  0.035410966  0.0009042886
wen14  0.0007226721  0.0040101430  0.011426186 -0.0034468308
wen15  0.0047501167  0.0279620798 -0.032026475  0.0118456443
wen16  0.0237185028 -0.0002357627 -0.015609289  0.0293600091
wen17  0.5346715355  0.0261360468 -0.016940365  0.0229904098
wen18  0.0261360468  0.3345794835 -0.012970528  0.0359288395
wen19 -0.0169403652 -0.0129705285  0.282819500 -0.0202929218
wen21  0.0229904098  0.0359288395 -0.020292922  0.3721188611

$dof
[1] 117

$chi
[1] 220.4391

$nh
[1] 1097

$rms
[1] 0.02423974

$EPVAL
[1] 2.430039e-08

> View(df)
>
```



26 Define the three factors based upon the variable's column *N*

```
> factor1<-df[ , c(2,8,11,12,14,17,18,19)]
> factor2<-df[ , c(1,4,5,7,9,13,15)]
> factor3<-df[ , c(3, 6, 10, 16)]
```

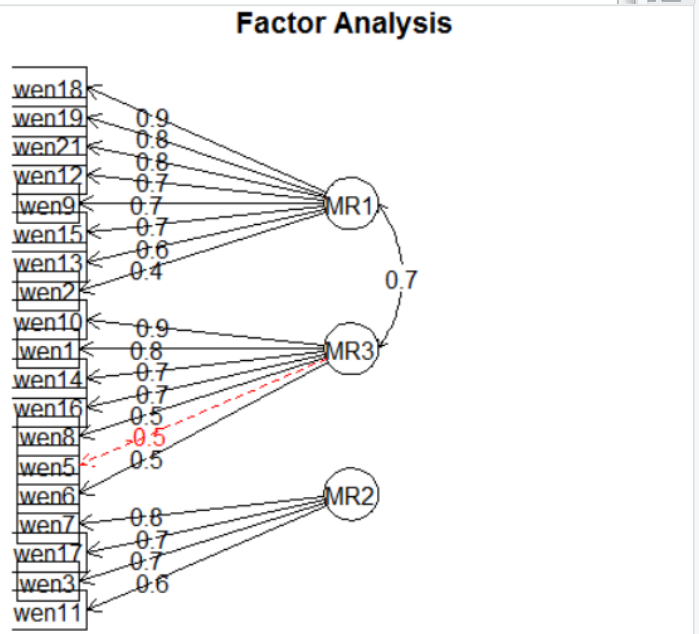
RStudio

File Edit Code View Plots Session Build Debug Profile Tools Help

Go to file/function | Addins | Project: (None)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
	wen1	wen2	wen3	wen5	wen6	wen7	wen8	wen9	wen10	wen11	wen12	wen13	wen14	wen15	wen16	wen17	wen18	wen19	wen21
1	5	5	4	4	5	4	5	5	5	4	5	5	5	4	5	5	5	5	5
				2	2	3	2	3	4	2	3	3	4	2	4	2	3	3	4
				3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
				2	4	3	4	4	2	2	4	5	4	4	3	2	4	4	4
				1	5	3	5	5	5	2	4	5	5	5	5	4	5	5	5
				1	4	3	4	3	5	3	5	5	5	3	5	3	3	3	5

```
wen9   -0.0253105364 -0.0359215569  0.037087635 -0.0177528029
wen10   0.0133567073  0.0157788116 -0.011662946   0.0198706776
wen11   0.0441446138  0.0343384712 -0.033213983  -0.0004973291
wen12   0.0178133094  0.0560385897 -0.059669048   0.0188425009
wen13   0.0034911709 -0.0153449022  0.035410966   0.0009042886
wen14   0.0007226721  0.0040101430  0.011426186  -0.0034468308
wen15   0.0047501167  0.0279620798 -0.032026475   0.0118456443
wen16   0.0237185028 -0.0002357627 -0.015609289   0.0293600091
wen17   0.5346715355  0.0261360468 -0.016940365   0.0229904098
wen18   0.0261360468  0.3345794835 -0.012970528   0.0359288395
wen19  -0.0169403652 -0.0129705285  0.282819500  -0.0202929218
wen21   0.0229904098  0.0359288395 -0.020292922   0.3721188611

$dof
[1] 117

$chi
[1] 220.4391

$nh
[1] 1097

$rms
[1] 0.02423974

$EPVAL
[1] 2.430039e-08

> View(df)
>
```



27 Assess the reliability for factor 1

> Alpha(factor1)