

Fiche de modélisations n°6

Variables et classes latentes

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1 Objectif

L'objectif de cette sixième série de modèles est de ...

2 Analyses

TODO

3 Code et résultats

```
#chargement des packages
library(knitr)
library(dplyr) #manipuler les bases de données
library(psych) #EFA
library(lavaan) #CFA et SEM
library(semPlot) #path draw CFA SEM
library(poLCA) #pour les Latent Categorical Variables
```

```
library(ade4) #pour la fonction s5 de plot des classes de CAH  
library(RColorBrewer) #palettes de couleur  
library(ggplot2) #graphiques corrplot  
library(tidyr) #pour pivot_longer / wider  
library(tibble) #pour rownames_to_column
```

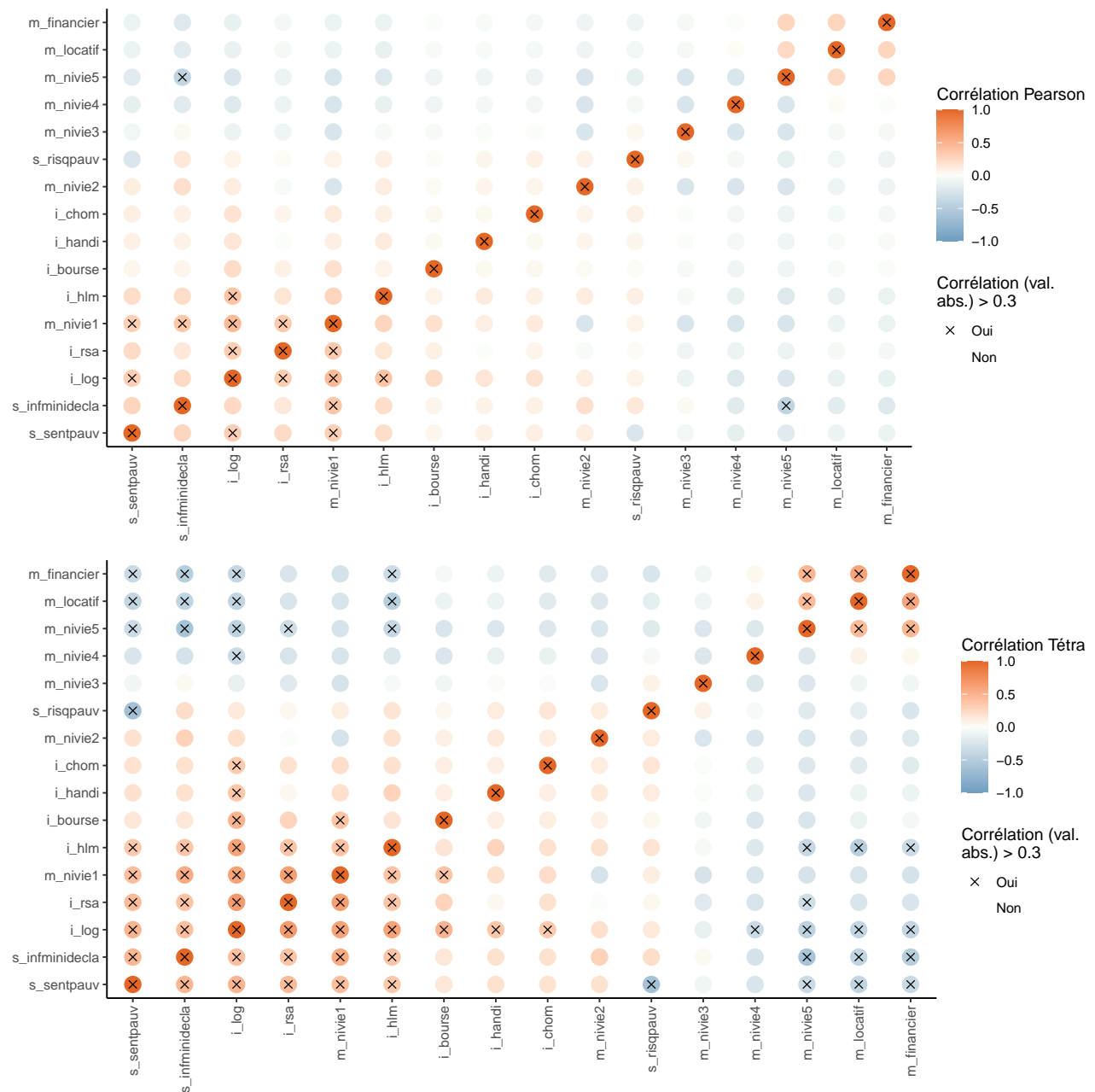
3.1 Correlation coefficients

A correlation coefficient suited for dichotomous data and based on this underlying normal strategy is the tetrachoric correlation. It gives us a single number describing the degree of dependence in the table above with the extreme values of 1 if the off-diagonals are 0 and -1 if the diagonals are 0. In addition, we get estimates for the thresholds τ_1 and τ_2 . polychoric existe aussi pour deux items polytomous.

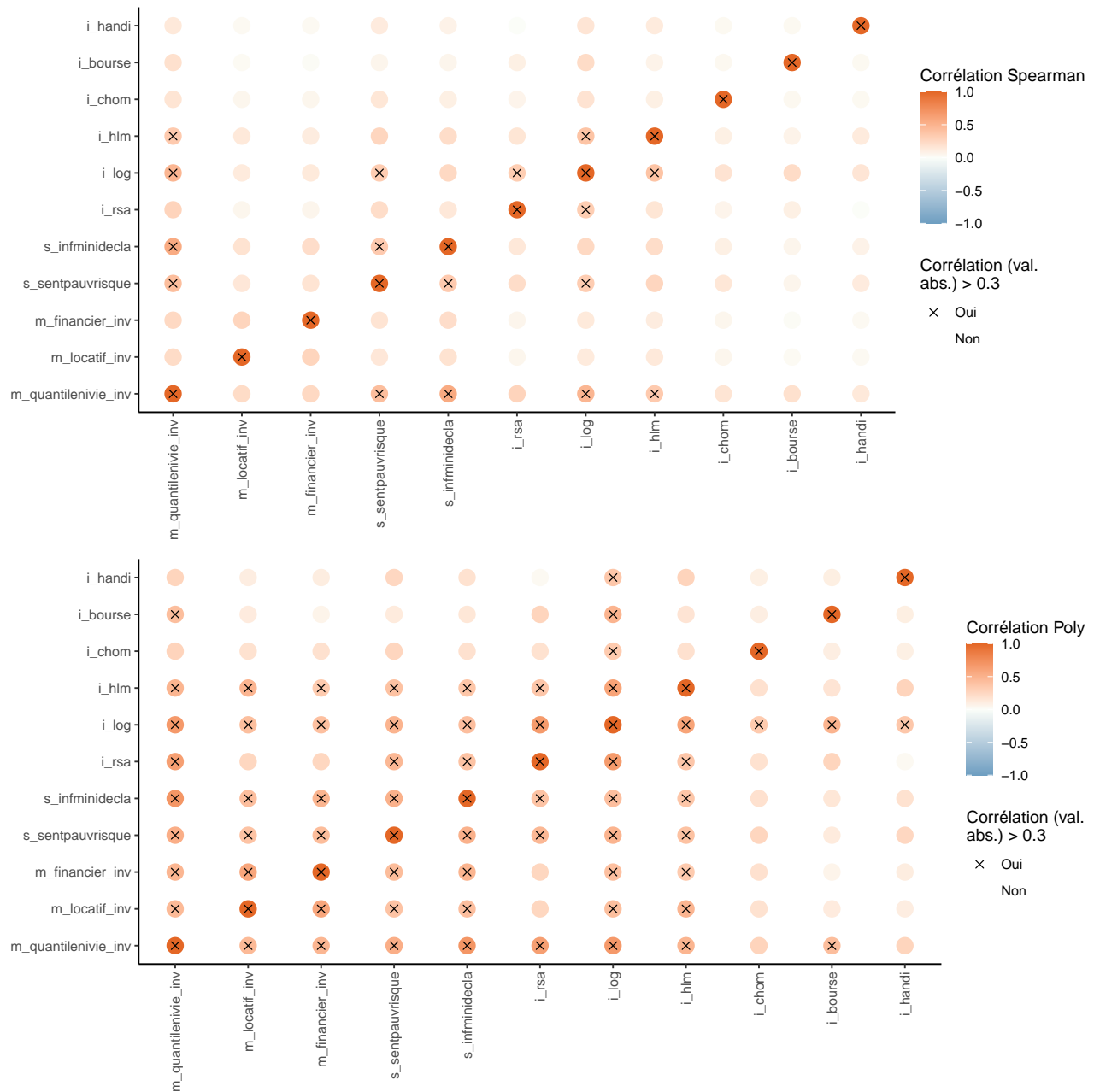
We print out the last six eigenvalues and see that the last eigenvalue is negative. Thus, this matrix does not fulfill the properties of a correlation matrix. The trick is now to apply some smoothing on the correlations.

The final criterion is interpretability.

3.1.1 Indicatrices



3.1.2 Variables catégorielles (plus de 2 modalités possibles)



3.2 Exploratory Factor Analysis (EFA)

However, in order to get an even clearer picture, in EFA we typically apply a rotation on the loadings matrix. Such a rotation does not change the fit of the model; it is only done for interpretation purposes by transforming the loadings. We distinguish between two basic types of rotations: orthogonal (qui implique que les facteurs sont indépendants) and nonorthogonal rotation (comme oblimin).

In practice, EFA with oblique rotation is often used prior to a CFA in order to explore whether the underlying latent structure theory is reflected by the data.

Différences entre EFA et ACP - Les ACP reposent sur des estimations bien plus simples que les EFA (ML, LS). - L'EFA se concentrent sur l'explication des termes en dehors de la diagonales

des éléments de grand sigma (explique les covariances) alors que l'ACP se concentre sur la diagonale (explique principalement la variance, même si pas totalement aveugle aux covariances). - Les scores des facteurs sont calculés post hoc alors que ceux de l'ACP est une conséquence directe du SVD. - En EFA, on fixe p avant de faire tourner le modèle, dans l'ACP on choisit le nombre d'axes a posteriori. - En EFA, les rotations peuvent aider à mieux interpréter sans changer la solution, contrairement à la PCA pour laquelle la solution est changée.

PCA et EFA sont deux techniques de réduction de dimensions mais elles ont des différences.

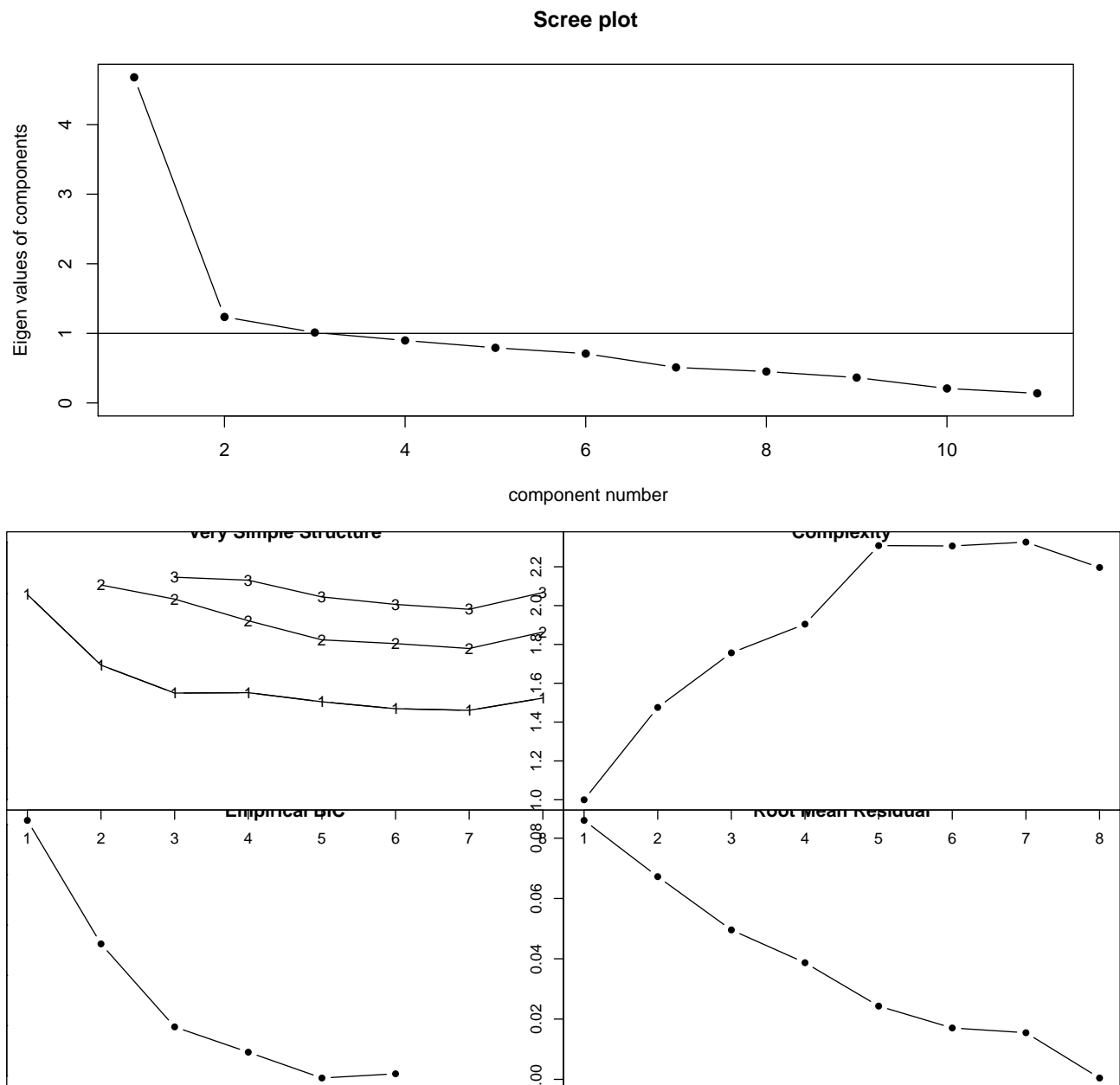
On utilise la PCA quand les variables sont très corrélées cela permet de réduire le nombre de variables observées en un plus petit nombre de composantes principales qui résument un maximum de variances des variables observées On utilise l'EFA pour identifier le nombre de variables latentes (non mesurée directement) et la structure des facteurs qui découlent d'un ensemble de variables. Elle permet d'estimer les facteurs qui influencent les réponses des variables observées.

Unlike factor analysis, principal components analysis or PCA makes the assumption that there is no unique variance, the total variance is equal to common variance. Recall that variance can be partitioned into common and unique variance. If there is no unique variance then common variance takes up total variance (see figure below). Additionally, if the total variance is 1, then the common variance is equal to the communality.

- PCA suppose l'absence d'outliers. L'EFA suppose une distribution normale multivariée quand la méthode de ML est utilisée
- Les axes de la PCA tiennent compte de la variance maximale des variables observées alors que les facteurs de l'EFA tiennent compte de la variance commune
- La PCA utilise une matrice de corrélation alors que l'EFA utilise une matrice de corrélation ajustée
- Dans une PCA il y a des 1 sur la diagonale de la matrice de corrélation alors que dans l'EFA la diagonale est ajustée avec les facteurs uniques.
- La PCA minimise la somme des carrés perpendiculaire à la distance aux axes des composantes. L'EFA estime des facteurs qui influencent la réponse à des variables observées.
- Les scores des composantes de la PCA est une combinaison linéaire des variables observées pondérées par les vecteurs propres. Les variables observées de l'EFA sont une combinaison linéaire des facteurs uniques

n alternative to factor analysis, which is unfortunately frequently confused with factor analysis, is principal components analysis. Although the goals of PCA and FA are similar, PCA is a descriptive model of the data, while FA is a structural model. Psychologists typically use PCA in a manner similar to factor analysis and thus the principal function produces output that is perhaps more understandable than that produced by princomp in the stats package. Table 4 shows a PCA of the Thurstone 9 variable problem rotated using the Promax function. Note how the loadings from the factor model are similar but smaller than the principal component loadings. This is because the PCA model attempts to account for the entire variance of the correlation matrix, while FA accounts for just the common variance. This distinction becomes most important for small correlation matrices. Also note how the goodness of fit statistics, based upon the residual off diagonal elements, is much worse than the factor solution.

[1] 42.54 11.24 9.20 8.16 7.20 6.44 4.64 4.10 3.31 1.90 1.26



Factor analysis with Call: `fa(r = bdd_poLCA_poly$rho, nfactors = 2, rotate = "oblimin", scores = "regression", missing = TRUE, impute = "median", fm = "ml", cor = "poly")`

Test of the hypothesis that 2 factors are sufficient.
 The degrees of freedom for the model is 34 and the objective function was 0.81

The root mean square of the residuals (RMSA) is 0.07
 The df corrected root mean square of the residuals is 0.09

With factor correlations of
 ML2 ML1

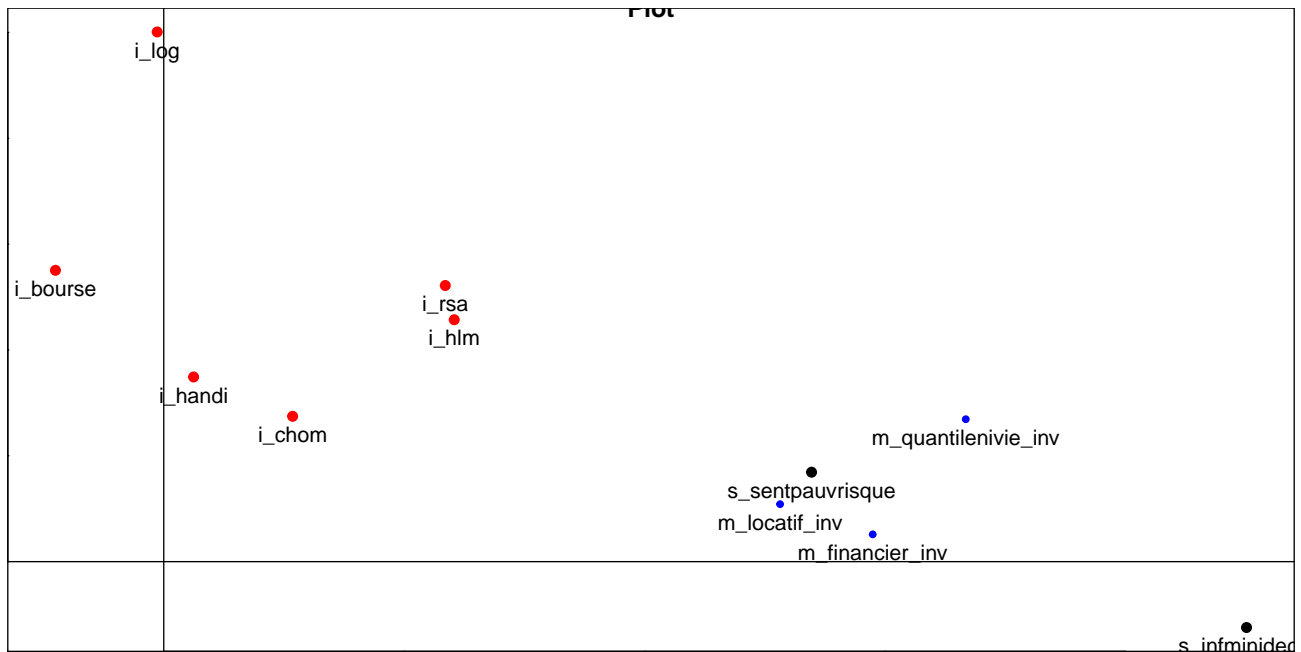
ML2 1.00 0.61
ML1 0.61 1.00

Loadings:

	ML2	ML1
s_senpauvrisque	0.539	
s_infminidecla	0.901	
m_quantilenivie_inv	0.668	
m_locatif_inv	0.513	
m_financier_inv	0.590	
i_log		1.001
i_rsa		0.522
i_chom		
i_handi		0.349
i_bourse		0.550
i_hlm		0.457

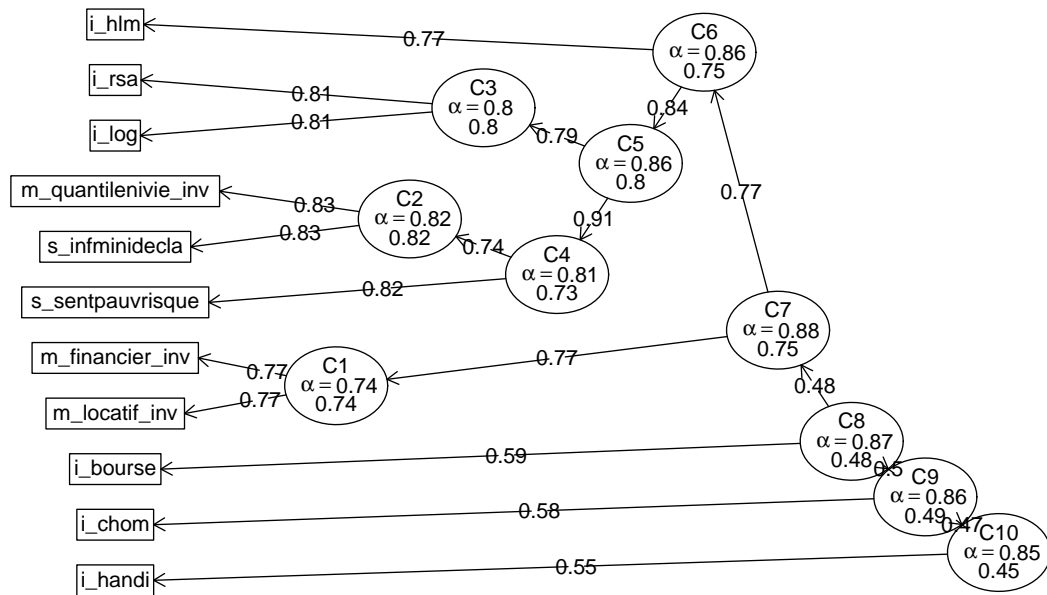
	ML2	ML1
SS loadings	2.294	2.114
Proportion Var	0.209	0.192
Cumulative Var	0.209	0.401

s_senpauvrisque	s_infminidecla	m_quantilenivie_inv	m_locatif_inv
0.43	0.69	0.74	0.34
m_financier_inv	i_log	i_rsa	i_chom
0.39	1.00	0.48	0.12
i_handi	i_bourse	i_hlm	
0.13	0.25	0.40	



Premier type de clustering (de variables et non d'individus) avec iclust

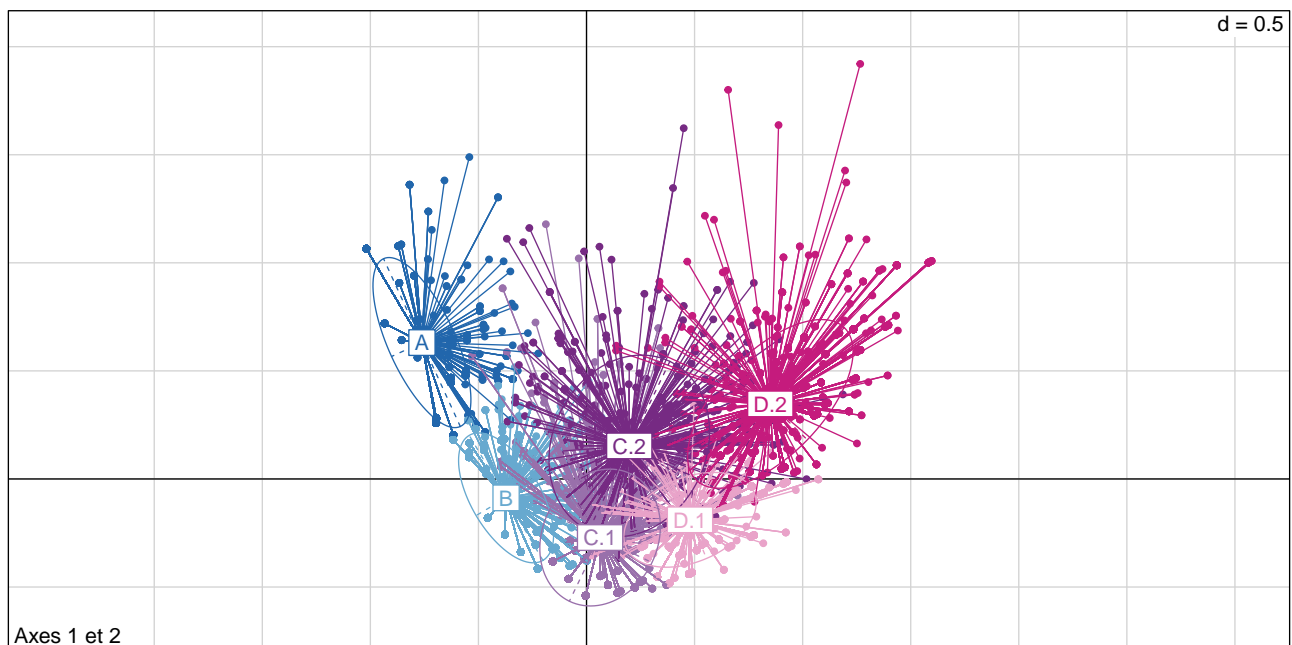
ICLUST using polychoric correlations



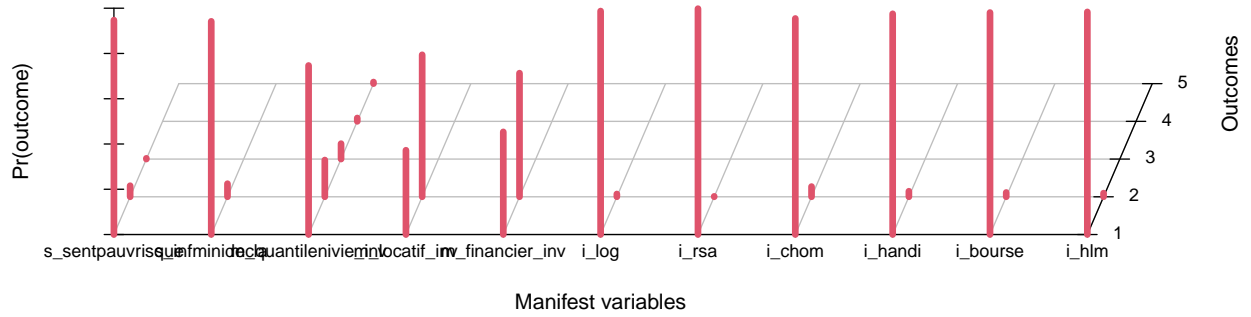
3.3 Latent Categorical Variables

Source : <https://m-clark.github.io/sem/mixture-models.html>

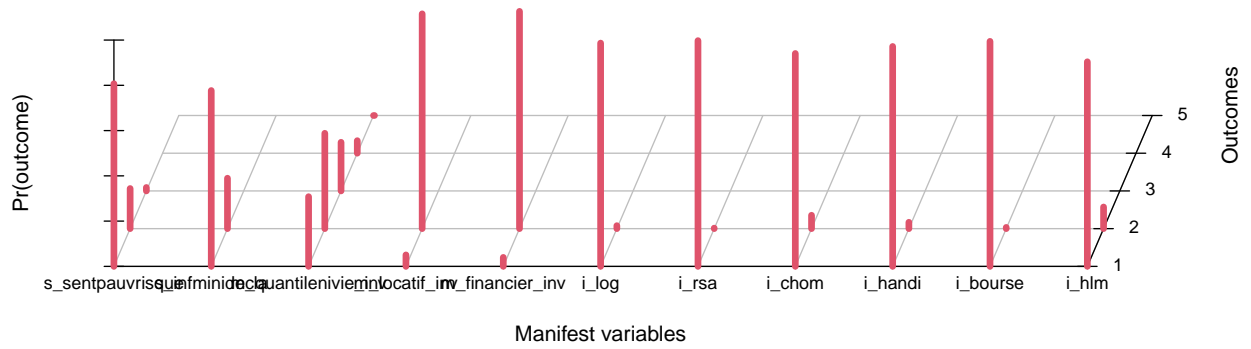
Documentation <https://raw.githubusercontent.com/dlinzer/poLCA/master/inst/doc/poLCA-manual-1-4.pdf>



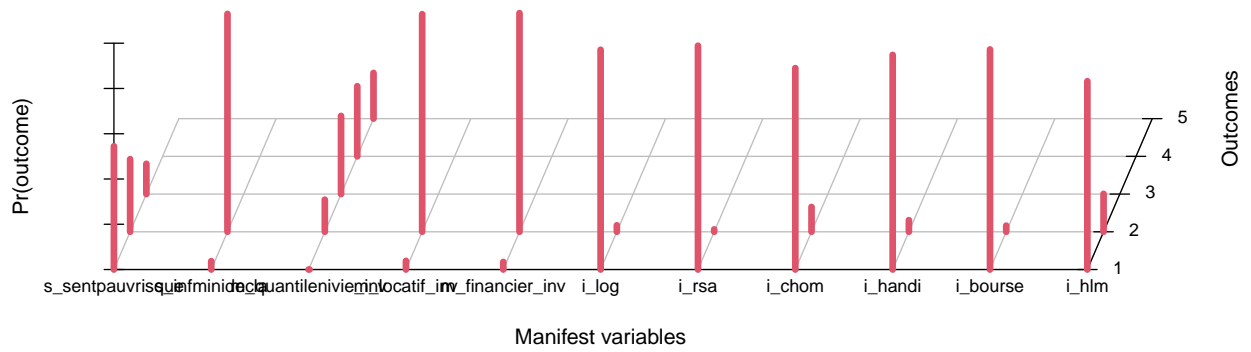
Classe A : part de la population = 12.8 %



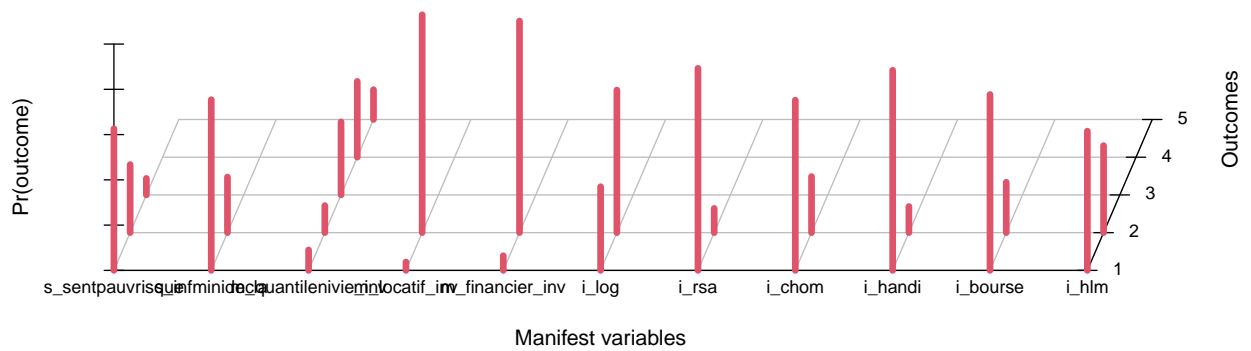
Classe B : part de la population = 30.5 %



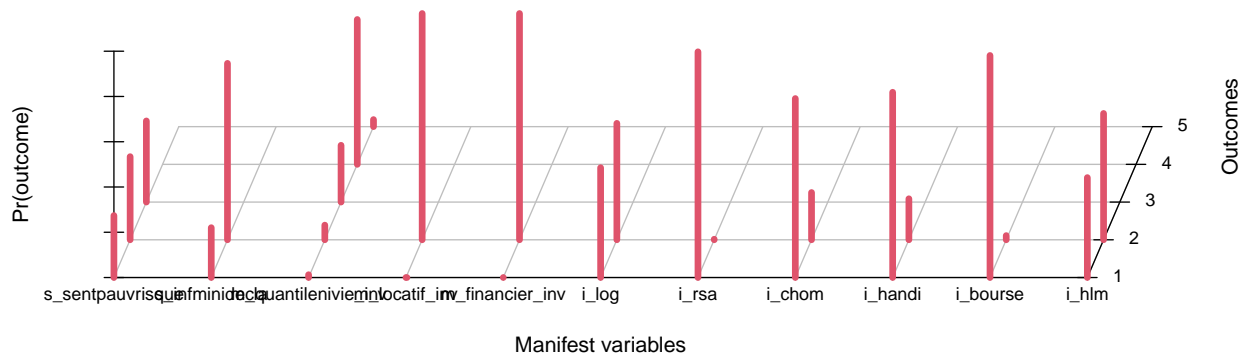
Classe C.1 : part de la population = 23.3 %



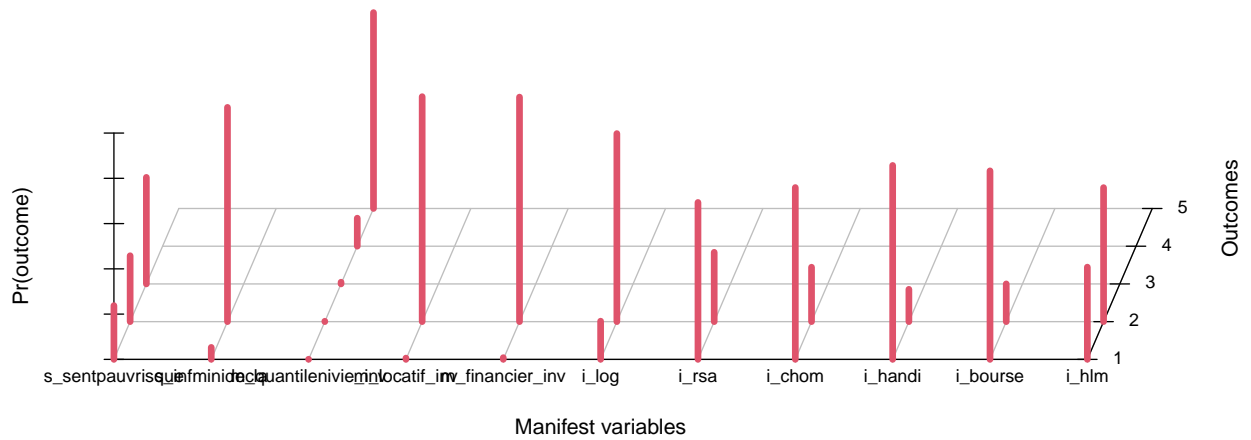
Classe C.2 : part de la population = 7.2 %



Classe D.1 : part de la population = 9.9 %



Classe D.2 : part de la population = 16.3 %

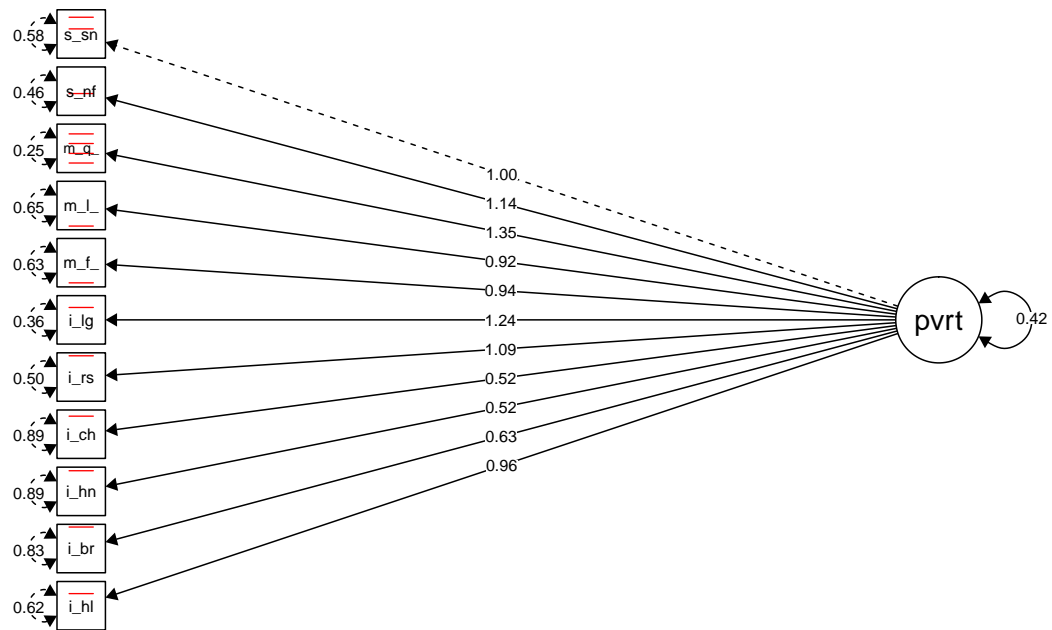


A1(bleu foncé) : Très riches A2(bleu moyen) : Riches B1 (violet foncé) : Q1 Q3 / **pas infminidecla** / pauvetrisque / **insti** B2(violet clair): Q1 Q3 / **infminidecla enorm** / pauvetrisque / **pas insti**
 C2(rose clair): Q1/ infminidecla / **sent pauv et risque** / **peu insti** C1(rose foncé) : Q2 / infminidecla / **sent pauv** / **inst**

3.4 Confirmatory factor analysis (CFA) des dimensions de la pauvreté

EFA and CFA are mathematically very similar, since we have the same fundamental equation in both cases. In EFA we assumed uncorrelated factors by setting

3.4.1 Modèle sans dimensions de la pauvreté



lavaan 0.6-8 ended normally after 19 iterations

Estimator	DWLS
Optimization method	NLMINB
Number of model parameters	26
Number of observations	13359

Model Test User Model:

	Standard	Robust
Test Statistic	1142.455	1398.800
Degrees of freedom	44	44
P-value (Chi-square)	0.000	0.000
Scaling correction factor		0.819
Shift parameter		3.550
simple second-order correction		

Model Test Baseline Model:

Test statistic	53597.773	43159.977
Degrees of freedom	55	55
P-value	0.000	0.000
Scaling correction factor		1.242

User Model versus Baseline Model:

Comparative Fit Index (CFI)	0.979	0.969
Tucker-Lewis Index (TLI)	0.974	0.961

Robust Comparative Fit Index (CFI)	NA
Robust Tucker-Lewis Index (TLI)	NA

Root Mean Square Error of Approximation:

RMSEA	0.043	0.048
90 Percent confidence interval - lower	0.041	0.046
90 Percent confidence interval - upper	0.045	0.050
P-value RMSEA <= 0.05	1.000	0.933

Robust RMSEA	NA
90 Percent confidence interval - lower	NA
90 Percent confidence interval - upper	NA

Standardized Root Mean Square Residual:

SRMR	0.079	0.079
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Parameter Estimates:

Standard errors	Robust.sem
Information	Expected
Information saturated (h1) model	Unstructured

Latent Variables:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
pauvrete =~						
s_senpauvrisq	1.000				0.645	0.645
s_infinidecla	1.142	0.018	64.093	0.000	0.736	0.736
m_quantilnv_nv	1.346	0.018	73.191	0.000	0.868	0.868
m_locatif_inv	0.921	0.025	36.913	0.000	0.594	0.594
m_financier_nv	0.942	0.024	39.561	0.000	0.607	0.607
i_log	1.241	0.018	68.625	0.000	0.800	0.800
i_rsa	1.092	0.021	51.013	0.000	0.704	0.704
i_chom	0.518	0.022	23.300	0.000	0.334	0.334
i_handi	0.519	0.026	20.002	0.000	0.335	0.335
i_bourse	0.632	0.027	23.774	0.000	0.408	0.408
i_hlm	0.956	0.018	51.721	0.000	0.616	0.616

Intercepts:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
.s_senpauvrisq	0.000				0.000	0.000
.s_infinidecla	0.000				0.000	0.000
.m_quantilnv_nv	0.000				0.000	0.000
.m_locatif_inv	0.000				0.000	0.000
.m_financier_nv	0.000				0.000	0.000
.i_log	0.000				0.000	0.000
.i_rsa	0.000				0.000	0.000
.i_chom	0.000				0.000	0.000

.i_handi	0.000			0.000	0.000
.i_bourse	0.000			0.000	0.000
.i_hlm	0.000			0.000	0.000
pauvrete	0.000			0.000	0.000

Thresholds:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
s_sentpvrsq t1	0.267	0.011	24.326	0.000	0.267	0.267
s_sentpvrsq t2	1.020	0.013	77.484	0.000	1.020	1.020
s_infmindcl t1	-0.123	0.011	-11.357	0.000	-0.123	-0.123
m_qntlnv_nv t1	-0.852	0.012	-68.664	0.000	-0.852	-0.852
m_qntlnv_nv t2	-0.266	0.011	-24.223	0.000	-0.266	-0.266
m_qntlnv_nv t3	0.252	0.011	22.964	0.000	0.252	0.252
m_qntlnv_nv t4	0.836	0.012	67.760	0.000	0.836	0.836
m_locatf_nv t1	-1.435	0.016	-89.369	0.000	-1.435	-1.435
m_finncr_nv t1	-1.380	0.016	-88.614	0.000	-1.380	-1.380
i_log t1	0.693	0.012	58.531	0.000	0.693	0.693
i_rsa t1	1.543	0.017	90.111	0.000	1.543	1.543
i_chom t1	1.139	0.014	82.368	0.000	1.139	1.139
i_handi t1	1.451	0.016	89.539	0.000	1.451	1.451
i_bourse t1	1.593	0.018	90.139	0.000	1.593	1.593
i_hlm t1	0.675	0.012	57.238	0.000	0.675	0.675

Variances:

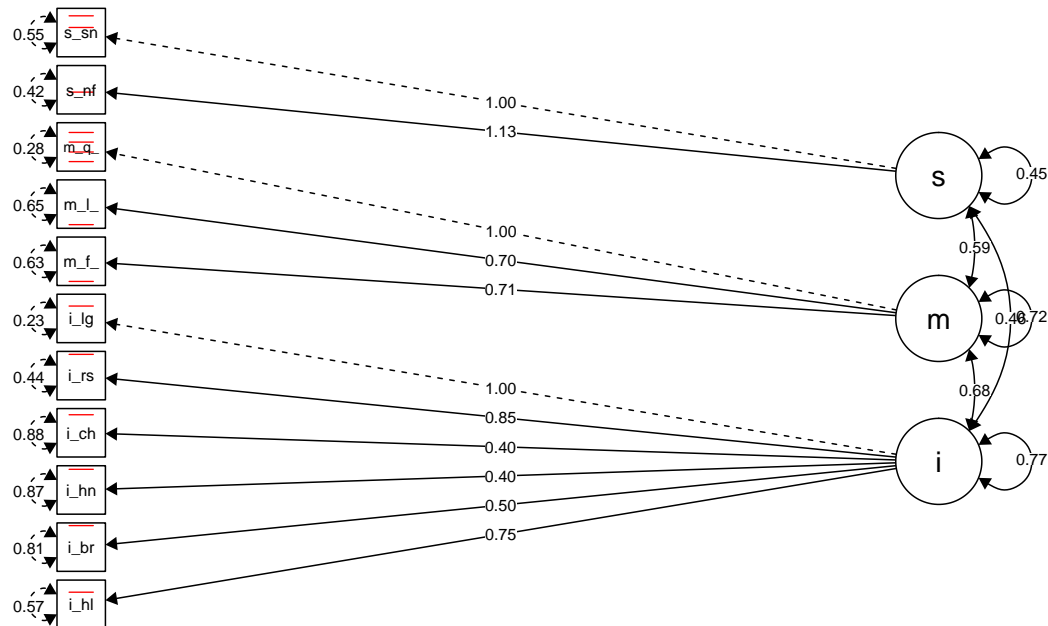
	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
.s_senpauvrisq	0.584				0.584	0.584
.s_infminidecla	0.458				0.458	0.458
.m_quantilnv_nv	0.246				0.246	0.246
.m_locatif_inv	0.647				0.647	0.647
.m_financier_nv	0.631				0.631	0.631
.i_log	0.359				0.359	0.359
.i_rsa	0.504				0.504	0.504
.i_chom	0.888				0.888	0.888
.i_handi	0.888				0.888	0.888
.i_bourse	0.834				0.834	0.834
.i_hlm	0.620				0.620	0.620
pauvrete	0.416	0.010	40.495	0.000	1.000	1.000

Scales y*:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
s_senpauvrisq	1.000				1.000	1.000
s_infminidecla	1.000				1.000	1.000
m_quantilnv_nv	1.000				1.000	1.000
m_locatif_inv	1.000				1.000	1.000
m_financier_nv	1.000				1.000	1.000
i_log	1.000				1.000	1.000
i_rsa	1.000				1.000	1.000
i_chom	1.000				1.000	1.000
i_handi	1.000				1.000	1.000

i_bourse	1.000	1.000	1.000
i_hlm	1.000	1.000	1.000

3.4.2 Modèle avec 3 dimensions de la pauvreté (i,m,s)



lavaan 0.6-8 ended normally after 22 iterations

Estimator	DWLS
Optimization method	NLMINB
Number of model parameters	29
Number of observations	13359

Model Test User Model:

	Standard	Robust
Test Statistic	792.116	979.597
Degrees of freedom	41	41
P-value (Chi-square)	0.000	0.000
Scaling correction factor		0.811
Shift parameter		2.975
simple second-order correction		

Model Test Baseline Model:

Test statistic	53597.773	43159.977
Degrees of freedom	55	55
P-value	0.000	0.000
Scaling correction factor		1.242

User Model versus Baseline Model:

Comparative Fit Index (CFI)	0.986	0.978
Tucker-Lewis Index (TLI)	0.981	0.971
Robust Comparative Fit Index (CFI)		NA
Robust Tucker-Lewis Index (TLI)		NA

Root Mean Square Error of Approximation:

RMSEA	0.037	0.041
90 Percent confidence interval - lower	0.035	0.039
90 Percent confidence interval - upper	0.039	0.044
P-value RMSEA <= 0.05	1.000	1.000
Robust RMSEA		NA
90 Percent confidence interval - lower		NA
90 Percent confidence interval - upper		NA

Standardized Root Mean Square Residual:

SRMR	0.073	0.073
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Parameter Estimates:

Standard errors	Robust.sem
Information	Expected
Information saturated (h1) model	Unstructured

Latent Variables:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
s =~						
s_senpauvrisq	1.000				0.674	0.674
s_infinidecla	1.132	0.018	63.490	0.000	0.763	0.763
m =~						
m_quantilnv_nv	1.000				0.846	0.846
m_locatif_inv	0.698	0.019	36.523	0.000	0.590	0.590
m_financier_nv	0.714	0.018	39.366	0.000	0.604	0.604
i =~						
i_log	1.000				0.880	0.880
i_rsa	0.847	0.015	55.299	0.000	0.746	0.746
i_chom	0.401	0.017	23.587	0.000	0.353	0.353
i_handi	0.403	0.020	20.465	0.000	0.355	0.355
i_bourse	0.497	0.020	25.268	0.000	0.437	0.437
i_hlm	0.746	0.013	56.923	0.000	0.656	0.656

Covariances:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
s ~~						
m	0.589	0.008	74.532	0.000	1.034	1.034

i	0.462	0.009	50.563	0.000	0.779	0.779
m ~						
i	0.681	0.008	90.677	0.000	0.916	0.916

Intercepts:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
.s_senpauvrisq	0.000				0.000	0.000
.s_infminidecla	0.000				0.000	0.000
.m_quantilnv_nv	0.000				0.000	0.000
.m_locatif_inv	0.000				0.000	0.000
.m_financier_nv	0.000				0.000	0.000
.i_log	0.000				0.000	0.000
.i_rsa	0.000				0.000	0.000
.i_chom	0.000				0.000	0.000
.i_handi	0.000				0.000	0.000
.i_bourse	0.000				0.000	0.000
.i_hlm	0.000				0.000	0.000
s	0.000				0.000	0.000
m	0.000				0.000	0.000
i	0.000				0.000	0.000

Thresholds:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
s_senpvrsq t1	0.267	0.011	24.326	0.000	0.267	0.267
s_senpvrsq t2	1.020	0.013	77.484	0.000	1.020	1.020
s_infmindcl t1	-0.123	0.011	-11.357	0.000	-0.123	-0.123
m_qntlnv_nv t1	-0.852	0.012	-68.664	0.000	-0.852	-0.852
m_qntlnv_nv t2	-0.266	0.011	-24.223	0.000	-0.266	-0.266
m_qntlnv_nv t3	0.252	0.011	22.964	0.000	0.252	0.252
m_qntlnv_nv t4	0.836	0.012	67.760	0.000	0.836	0.836
m_locatf_nv t1	-1.435	0.016	-89.369	0.000	-1.435	-1.435
m_finnr_nv t1	-1.380	0.016	-88.614	0.000	-1.380	-1.380
i_log t1	0.693	0.012	58.531	0.000	0.693	0.693
i_rsa t1	1.543	0.017	90.111	0.000	1.543	1.543
i_chom t1	1.139	0.014	82.368	0.000	1.139	1.139
i_handi t1	1.451	0.016	89.539	0.000	1.451	1.451
i_bourse t1	1.593	0.018	90.139	0.000	1.593	1.593
i_hlm t1	0.675	0.012	57.238	0.000	0.675	0.675

Variances:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
.s_senpauvrisq	0.546				0.546	0.546
.s_infminidecla	0.418				0.418	0.418
.m_quantilnv_nv	0.285				0.285	0.285
.m_locatif_inv	0.652				0.652	0.652
.m_financier_nv	0.635				0.635	0.635
.i_log	0.226				0.226	0.226
.i_rsa	0.444				0.444	0.444
.i_chom	0.875				0.875	0.875

.i_handi	0.874				0.874	0.874
.i_bourse	0.809				0.809	0.809
.i_hlm	0.569				0.569	0.569
s	0.454	0.012	37.338	0.000	1.000	1.000
m	0.715	0.015	46.200	0.000	1.000	1.000
i	0.774	0.014	55.899	0.000	1.000	1.000

Scales y*:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
s_senpauvrisq	1.000				1.000	1.000
s_infminidecla	1.000				1.000	1.000
m_quantilnv_nv	1.000				1.000	1.000
m_locatif_inv	1.000				1.000	1.000
m_financier_nv	1.000				1.000	1.000
i_log	1.000				1.000	1.000
i_rsa	1.000				1.000	1.000
i_chom	1.000				1.000	1.000
i_handi	1.000				1.000	1.000
i_bourse	1.000				1.000	1.000
i_hlm	1.000				1.000	1.000

- p-valeur du test du chi-2 de 0, très mauvais car un résultat non significatif veut dire que le modèle “fits” mais il ne faut pas faire très attention à cette statistique car elle est très souvent significative quand l’échantillon est grand.
- Le CFI doit être supérieur à 0,95.
- Le RMSEA doit être dans l’intervalle [0.05,0.10].
- Le SRMR doit être inférieur à 0.08.

3.4.3 Comment améliorer le modèle ?

lhs	op	rhs	est	se	z	pvalue	ci.lower	ci.upper
1	s =~	s_senpauvrisque	1.000	0.000	NA	NA	1.000	1.000
2	s =~	s_infminidecla	1.132	0.018	63.490	0	1.097	1.167
3	m =~	m_quantilenivie_inv	1.000	0.000	NA	NA	1.000	1.000
4	m =~	m_locatif_inv	0.698	0.019	36.523	0	0.660	0.735
5	m =~	m_financier_inv	0.714	0.018	39.366	0	0.679	0.750
6	i =~	i_log	1.000	0.000	NA	NA	1.000	1.000

id	lhs	rhs	nobs	row	col	obs.freq	obs.prop	est.prop
1	1 s_senpauvrisque	s_infminidecla	13359	1	1	4704	0.352	0.354
2	1 s_senpauvrisque	s_infminidecla	13359	2	1	1038	0.078	0.074
3	1 s_senpauvrisque	s_infminidecla	13359	3	1	281	0.021	0.023
4	1 s_senpauvrisque	s_infminidecla	13359	1	2	3383	0.253	0.251
5	1 s_senpauvrisque	s_infminidecla	13359	2	2	2179	0.163	0.167
6	1 s_senpauvrisque	s_infminidecla	13359	3	2	1774	0.133	0.131

X2

1	0.133
2	2.975
3	2.725
4	0.187

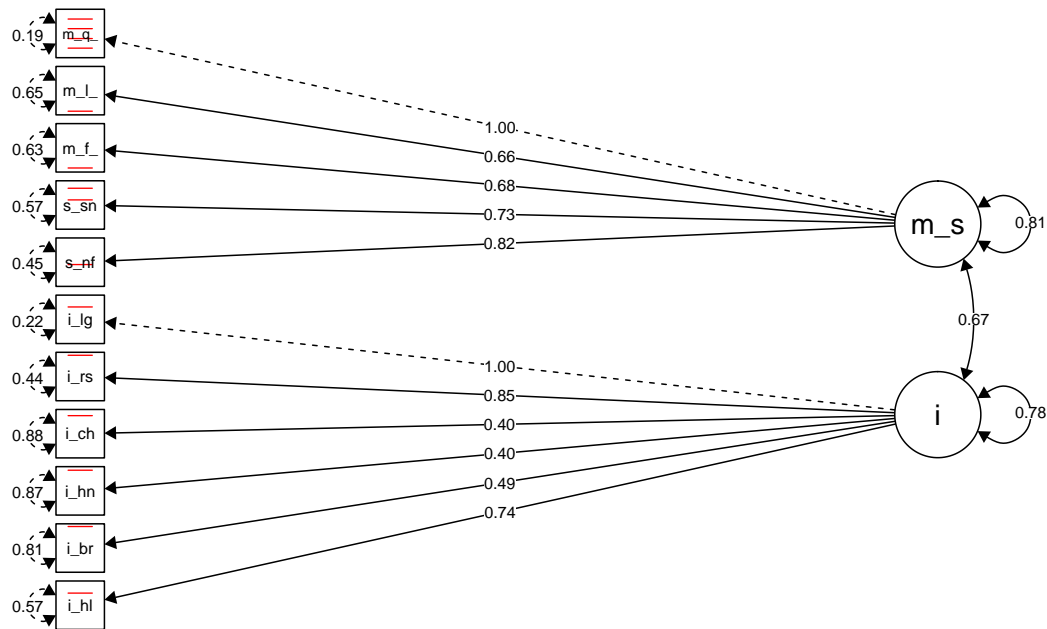
```

5 1.311
6 0.484

```

	lhs	op	rhs	mi	epc	sepc.lv	sepc.all
44	s_sen	~*	s_sen	32617.545	47.544	47.544	1.000
1	s	=~	s_sen	32617.545	47.544	32.032	32.032
78	m	=~	s_sen	12979.550	13.128	11.101	11.101
86	i	=~	s_sen	3597.071	3.394	2.986	2.986
101	s_in	~*	m_quant	926.292	0.378	0.378	1.097
45	s_in	~*	s_in	657.697	0.587	0.587	1.000
sepc.nox							
44	1.000						
1	32.032						
78	11.101						
86	2.986						
101	1.097						
45	1.000						

3.4.4 Modèle avec 2 dimensions de la pauvreté (i,m+s) comme dans EFA



lavaan 0.6-8 ended normally after 20 iterations

Estimator	DWLS
Optimization method	NLMINB
Number of model parameters	27
Number of observations	13359

Model Test User Model:

Test Statistic	Standard	Robust
	857.410	1054.887

Degrees of freedom	43	43
P-value (Chi-square)	0.000	0.000
Scaling correction factor		0.815
Shift parameter		3.368
simple second-order correction		

Model Test Baseline Model:

Test statistic	53597.773	43159.977
Degrees of freedom	55	55
P-value	0.000	0.000
Scaling correction factor		1.242

User Model versus Baseline Model:

Comparative Fit Index (CFI)	0.985	0.977
Tucker-Lewis Index (TLI)	0.981	0.970
Robust Comparative Fit Index (CFI)		NA
Robust Tucker-Lewis Index (TLI)		NA

Root Mean Square Error of Approximation:

RMSEA	0.038	0.042
90 Percent confidence interval - lower	0.035	0.040
90 Percent confidence interval - upper	0.040	0.044
P-value RMSEA <= 0.05	1.000	1.000
Robust RMSEA		NA
90 Percent confidence interval - lower		NA
90 Percent confidence interval - upper		NA

Standardized Root Mean Square Residual:

SRMR	0.072	0.072
------	-------	-------

Parameter Estimates:

Standard errors	Robust.sem
Information	Expected
Information saturated (h1) model	Unstructured

Latent Variables:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
m_s =~						
m_quantilnv_nv	1.000				0.900	0.900
m_locatif_inv	0.660	0.017	39.376	0.000	0.595	0.595
m_financier_nv	0.677	0.016	42.759	0.000	0.610	0.610
s_sentrpaupvrisq	0.727	0.010	70.919	0.000	0.654	0.654

s_infminidecla	0.823	0.011	74.334	0.000	0.741	0.741
i =~						
i_log	1.000				0.881	0.881
i_rsa	0.847	0.015	55.154	0.000	0.746	0.746
i_chom	0.401	0.017	23.604	0.000	0.353	0.353
i_handi	0.403	0.020	20.519	0.000	0.355	0.355
i_bourse	0.495	0.020	25.172	0.000	0.436	0.436
i_hlm	0.743	0.013	56.793	0.000	0.655	0.655

Covariances:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
m_s ~~						
i	0.670	0.007	89.840	0.000	0.845	0.845

Intercepts:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
.m_quantilnv_nv	0.000				0.000	0.000
.m_locatif_inv	0.000				0.000	0.000
.m_financier_nv	0.000				0.000	0.000
.s_senpauvrisq	0.000				0.000	0.000
.s_infminidecla	0.000				0.000	0.000
.i_log	0.000				0.000	0.000
.i_rsa	0.000				0.000	0.000
.i_chom	0.000				0.000	0.000
.i_handi	0.000				0.000	0.000
.i_bourse	0.000				0.000	0.000
.i_hlm	0.000				0.000	0.000
m_s	0.000				0.000	0.000
i	0.000				0.000	0.000

Thresholds:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
m_qntlnv_nv t1	-0.852	0.012	-68.664	0.000	-0.852	-0.852
m_qntlnv_nv t2	-0.266	0.011	-24.223	0.000	-0.266	-0.266
m_qntlnv_nv t3	0.252	0.011	22.964	0.000	0.252	0.252
m_qntlnv_nv t4	0.836	0.012	67.760	0.000	0.836	0.836
m_locatf_nv t1	-1.435	0.016	-89.369	0.000	-1.435	-1.435
m_finnr_nv t1	-1.380	0.016	-88.614	0.000	-1.380	-1.380
s_senpvrsq t1	0.267	0.011	24.326	0.000	0.267	0.267
s_senpvrsq t2	1.020	0.013	77.484	0.000	1.020	1.020
s_infmindcl t1	-0.123	0.011	-11.357	0.000	-0.123	-0.123
i_log t1	0.693	0.012	58.531	0.000	0.693	0.693
i_rsa t1	1.543	0.017	90.111	0.000	1.543	1.543
i_chom t1	1.139	0.014	82.368	0.000	1.139	1.139
i_handi t1	1.451	0.016	89.539	0.000	1.451	1.451
i_bourse t1	1.593	0.018	90.139	0.000	1.593	1.593
i_hlm t1	0.675	0.012	57.238	0.000	0.675	0.675

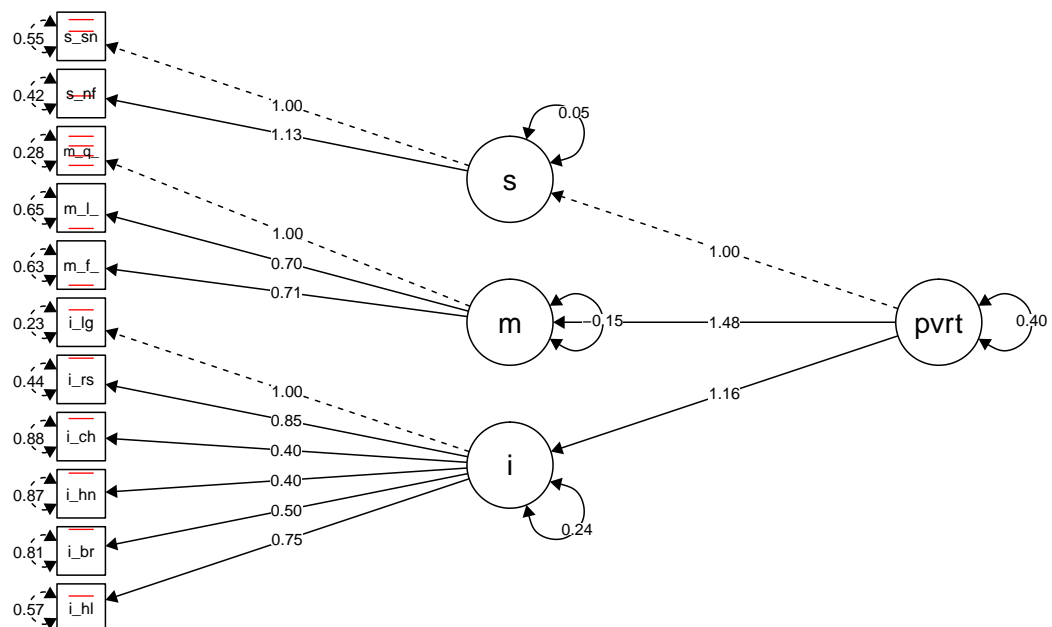
Variances:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
.m_quantilnv_nv	0.189				0.189	0.189
.m_locatif_inv	0.646				0.646	0.646
.m_financier_nv	0.628				0.628	0.628
.s_senpauvrisq	0.572				0.572	0.572
.s_infinidecla	0.451				0.451	0.451
.i_log	0.224				0.224	0.224
.i_rsa	0.443				0.443	0.443
.i_chom	0.875				0.875	0.875
.i_handi	0.874				0.874	0.874
.i_bourse	0.810				0.810	0.810
.i_hlm	0.571				0.571	0.571
m_s	0.811	0.010	82.529	0.000	1.000	1.000
i	0.776	0.014	55.869	0.000	1.000	1.000

Scales y*:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
m_quantilnv_nv	1.000				1.000	1.000
m_locatif_inv	1.000				1.000	1.000
m_financier_nv	1.000				1.000	1.000
s_senpauvrisq	1.000				1.000	1.000
s_infinidecla	1.000				1.000	1.000
i_log	1.000				1.000	1.000
i_rsa	1.000				1.000	1.000
i_chom	1.000				1.000	1.000
i_handi	1.000				1.000	1.000
i_bourse	1.000				1.000	1.000
i_hlm	1.000				1.000	1.000

3.4.5 CFA hiérarchique



lavaan 0.6-8 ended normally after 30 iterations

Estimator	DWLS
Optimization method	NLMINB
Number of model parameters	29
Number of observations	13359

Model Test User Model:

	Standard	Robust
Test Statistic	792.116	979.597
Degrees of freedom	41	41
P-value (Chi-square)	0.000	0.000
Scaling correction factor		0.811
Shift parameter		2.975
simple second-order correction		

Model Test Baseline Model:

Test statistic	53597.773	43159.977
Degrees of freedom	55	55
P-value	0.000	0.000
Scaling correction factor		1.242

User Model versus Baseline Model:

Comparative Fit Index (CFI)	0.986	0.978
Tucker-Lewis Index (TLI)	0.981	0.971
Robust Comparative Fit Index (CFI)		NA
Robust Tucker-Lewis Index (TLI)		NA

Root Mean Square Error of Approximation:

RMSEA	0.037	0.041
90 Percent confidence interval - lower	0.035	0.039
90 Percent confidence interval - upper	0.039	0.044
P-value RMSEA <= 0.05	1.000	1.000
Robust RMSEA		NA
90 Percent confidence interval - lower		NA
90 Percent confidence interval - upper		NA

Standardized Root Mean Square Residual:

SRMR	0.073	0.073
------	-------	-------

Parameter Estimates:

Standard errors	Robust.sem
Information	Expected
Information saturated (h1) model	Unstructured

Latent Variables:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
s =~						
s_senpauvrisq	1.000				0.674	0.674
s_infminidecla	1.132	0.018	63.490	0.000	0.763	0.763
m =~						
m_quantilnv_nv	1.000				0.846	0.846
m_locatif_inv	0.698	0.019	36.523	0.000	0.590	0.590
m_financier_nv	0.714	0.018	39.366	0.000	0.604	0.604
i =~						
i_log	1.000				0.880	0.880
i_rsa	0.847	0.015	55.299	0.000	0.746	0.746
i_chom	0.401	0.017	23.587	0.000	0.353	0.353
i_handi	0.403	0.020	20.465	0.000	0.355	0.355
i_bourse	0.497	0.020	25.268	0.000	0.437	0.437
i_hlm	0.746	0.013	56.923	0.000	0.656	0.656
pauvrete =~						
s	1.000				0.938	0.938
m	1.476	0.026	57.362	0.000	1.103	1.103
i	1.156	0.019	62.405	0.000	0.830	0.830

Intercepts:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
.s_senpauvrisq	0.000				0.000	0.000
.s_infminidecla	0.000				0.000	0.000
.m_quantilnv_nv	0.000				0.000	0.000
.m_locatif_inv	0.000				0.000	0.000
.m_financier_nv	0.000				0.000	0.000
.i_log	0.000				0.000	0.000
.i_rsa	0.000				0.000	0.000
.i_chom	0.000				0.000	0.000
.i_handi	0.000				0.000	0.000
.i_bourse	0.000				0.000	0.000
.i_hlm	0.000				0.000	0.000
.s	0.000				0.000	0.000
.m	0.000				0.000	0.000
.i	0.000				0.000	0.000
pauvrete	0.000				0.000	0.000

Thresholds:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
s_senpvrsq t1	0.267	0.011	24.326	0.000	0.267	0.267
s_senpvrsq t2	1.020	0.013	77.484	0.000	1.020	1.020
s_infmindcl t1	-0.123	0.011	-11.357	0.000	-0.123	-0.123
m_qntlnv_nv t1	-0.852	0.012	-68.664	0.000	-0.852	-0.852

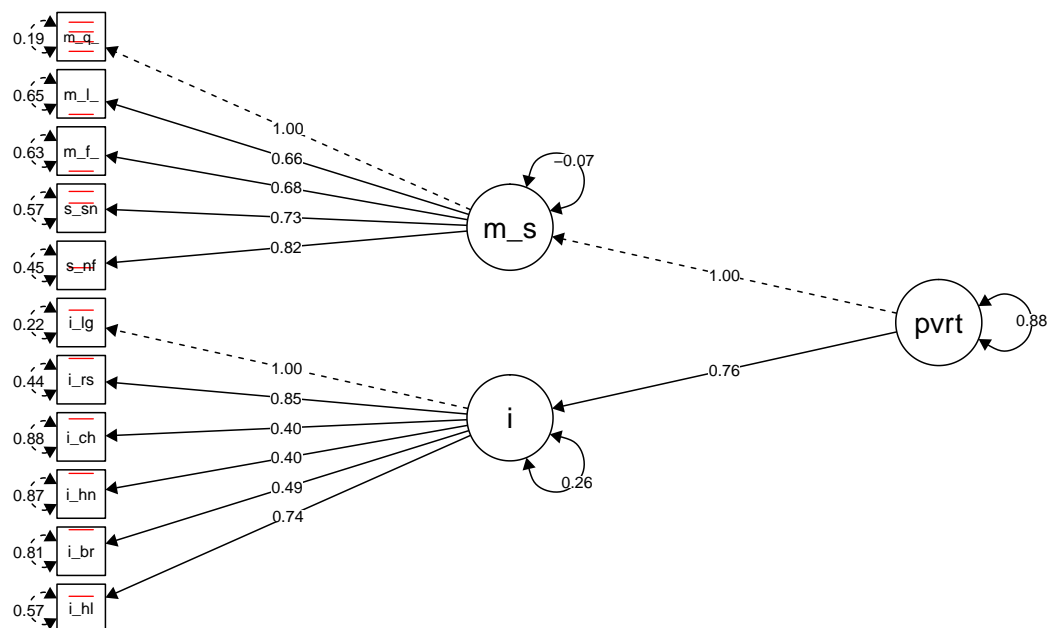
m_qntlnv_nv t2	-0.266	0.011	-24.223	0.000	-0.266	-0.266
m_qntlnv_nv t3	0.252	0.011	22.964	0.000	0.252	0.252
m_qntlnv_nv t4	0.836	0.012	67.760	0.000	0.836	0.836
m_locatf_nv t1	-1.435	0.016	-89.369	0.000	-1.435	-1.435
m_finnncr_nv t1	-1.380	0.016	-88.614	0.000	-1.380	-1.380
i_log t1	0.693	0.012	58.531	0.000	0.693	0.693
i_rsa t1	1.543	0.017	90.111	0.000	1.543	1.543
i_chom t1	1.139	0.014	82.368	0.000	1.139	1.139
i_handi t1	1.451	0.016	89.539	0.000	1.451	1.451
i_bourse t1	1.593	0.018	90.139	0.000	1.593	1.593
i_hlm t1	0.675	0.012	57.238	0.000	0.675	0.675

Variances:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
.s_senpauvrisq	0.546				0.546	0.546
.s_infminidecla	0.418				0.418	0.418
.m_quantilnv_nv	0.285				0.285	0.285
.m_locatif_inv	0.652				0.652	0.652
.m_financier_nv	0.635				0.635	0.635
.i_log	0.226				0.226	0.226
.i_rsa	0.444				0.444	0.444
.i_chom	0.875				0.875	0.875
.i_handi	0.874				0.874	0.874
.i_bourse	0.809				0.809	0.809
.i_hlm	0.569				0.569	0.569
.s	0.055	0.010	5.614	0.000	0.120	0.120
.m	-0.155	0.018	-8.516	0.000	-0.216	-0.216
.i	0.240	0.013	17.828	0.000	0.310	0.310
pauvrete	0.399	0.011	36.427	0.000	1.000	1.000

Scales y*:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
s_senpauvrisq	1.000				1.000	1.000
s_infminidecla	1.000				1.000	1.000
m_quantilnv_nv	1.000				1.000	1.000
m_locatif_inv	1.000				1.000	1.000
m_financier_nv	1.000				1.000	1.000
i_log	1.000				1.000	1.000
i_rsa	1.000				1.000	1.000
i_chom	1.000				1.000	1.000
i_handi	1.000				1.000	1.000
i_bourse	1.000				1.000	1.000
i_hlm	1.000				1.000	1.000



lavaan 0.6-8 ended normally after 20 iterations

Estimator	DWLS
Optimization method	NLMINB
Number of model parameters	28
Number of observations	13359

Model Test User Model:

	Standard	Robust
Test Statistic	857.410	857.410
Degrees of freedom	42	42
P-value (Chi-square)	0.000	0.000
Scaling correction factor		NA
Shift parameter		Robust

Model Test Baseline Model:

Test statistic	53597.773	43159.977
Degrees of freedom	55	55
P-value	0.000	0.000
Scaling correction factor		1.242

User Model versus Baseline Model:

Comparative Fit Index (CFI)	0.985	0.981
Tucker-Lewis Index (TLI)	0.980	0.975
Robust Comparative Fit Index (CFI)		NA

Robust Tucker-Lewis Index (TLI) NA

Root Mean Square Error of Approximation:

RMSEA	0.038	0.038
90 Percent confidence interval - lower	0.036	0.036
90 Percent confidence interval - upper	0.040	0.040
P-value RMSEA <= 0.05	1.000	1.000

Robust RMSEA	NA
90 Percent confidence interval - lower	NA
90 Percent confidence interval - upper	NA

Standardized Root Mean Square Residual:

SRMR	0.072	0.072
------	-------	-------

Parameter Estimates:

Standard errors	Robust.sem
Information	Expected
Information saturated (h1) model	Unstructured

Latent Variables:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
m_s =~						
m_quantilnv_nv	1.000				0.900	0.900
m_locatif_inv	0.660	NA			0.595	0.595
m_financier_nv	0.677	NA			0.610	0.610
s_sentpauvrisq	0.727	NA			0.654	0.654
s_infminidecla	0.823	NA			0.741	0.741
i =~						
i_log	1.000				0.881	0.881
i_rsa	0.847	NA			0.746	0.746
i_chom	0.401	NA			0.353	0.353
i_handi	0.403	NA			0.355	0.355
i_bourse	0.495	NA			0.436	0.436
i_hlm	0.743	NA			0.655	0.655
pauvrete =~						
m_s	1.000				1.041	1.041
i	0.763	NA			0.812	0.812

Intercepts:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
.m_quantilnv_nv	0.000				0.000	0.000
.m_locatif_inv	0.000				0.000	0.000
.m_financier_nv	0.000				0.000	0.000
.s_sentpauvrisq	0.000				0.000	0.000
.s_infminidecla	0.000				0.000	0.000

.i_log	0.000	0.000	0.000
.i_rsa	0.000	0.000	0.000
.i_chom	0.000	0.000	0.000
.i_handi	0.000	0.000	0.000
.i_bourse	0.000	0.000	0.000
.i_hlm	0.000	0.000	0.000
.m_s	0.000	0.000	0.000
.i	0.000	0.000	0.000
pauvrete	0.000	0.000	0.000

Thresholds:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
m_qntlnv_nv t1	-0.852	NA			-0.852	-0.852
m_qntlnv_nv t2	-0.266	NA			-0.266	-0.266
m_qntlnv_nv t3	0.252	NA			0.252	0.252
m_qntlnv_nv t4	0.836	NA			0.836	0.836
m_locatf_nv t1	-1.435	NA			-1.435	-1.435
m_finnr_nv t1	-1.380	NA			-1.380	-1.380
s_sentpvrsq t1	0.267	NA			0.267	0.267
s_sentpvrsq t2	1.020	NA			1.020	1.020
s_infmindcl t1	-0.123	NA			-0.123	-0.123
i_log t1	0.693	NA			0.693	0.693
i_rsa t1	1.543	NA			1.543	1.543
i_chom t1	1.139	NA			1.139	1.139
i_handi t1	1.451	NA			1.451	1.451
i_bourse t1	1.593	NA			1.593	1.593
i_hlm t1	0.675	NA			0.675	0.675

Variances:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
.m_quantilnv_nv	0.189				0.189	0.189
.m_locatif_inv	0.646				0.646	0.646
.m_financier_nv	0.628				0.628	0.628
.s_sentpauvrisq	0.572				0.572	0.572
.s_infminidecla	0.451				0.451	0.451
.i_log	0.224				0.224	0.224
.i_rsa	0.443				0.443	0.443
.i_chom	0.875				0.875	0.875
.i_handi	0.874				0.874	0.874
.i_bourse	0.810				0.810	0.810
.i_hlm	0.571				0.571	0.571
.m_s	-0.067	NA			-0.083	-0.083
.i	0.265	NA			0.341	0.341
pauvrete	0.878	NA			1.000	1.000

Scales y*:

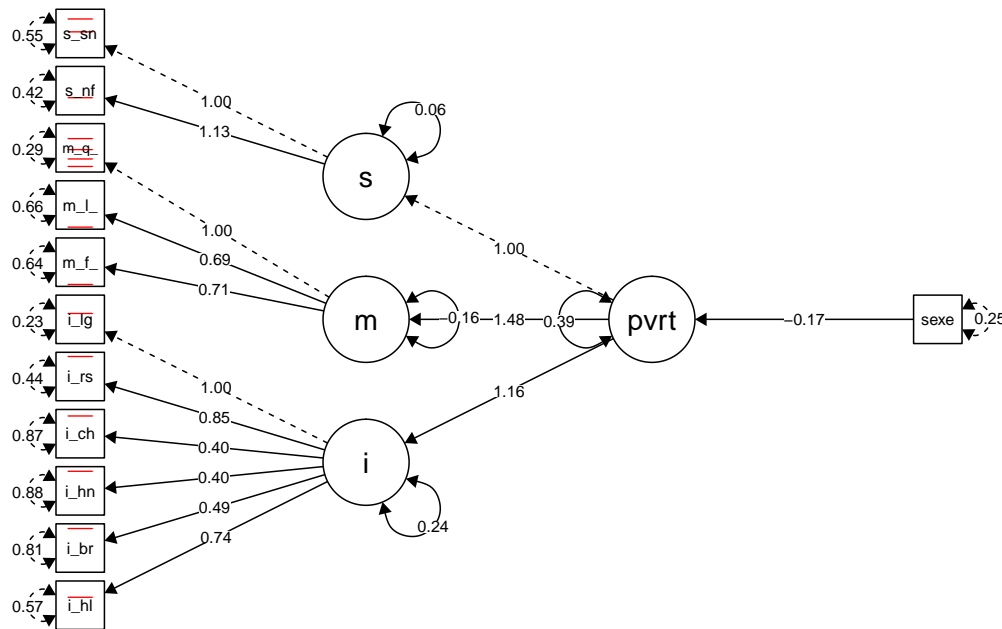
	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
m_quantilnv_nv	1.000				1.000	1.000
m_locatif_inv	1.000				1.000	1.000

m_financier_nv	1.000	1.000	1.000
s_senpauvrisq	1.000	1.000	1.000
s_infminidecla	1.000	1.000	1.000
i_log	1.000	1.000	1.000
i_rsa	1.000	1.000	1.000
i_chom	1.000	1.000	1.000
i_handi	1.000	1.000	1.000
i_bourse	1.000	1.000	1.000
i_hlm	1.000	1.000	1.000

3.5 CFA avec des covariables (MIMIC)

MIMIC stands for multiple indicators multiple independent causes (Jöreskog and Goldberger, 1975) and is a general structural latent variable concept where CFA is extended in terms of linking covariates with latent variables. MIMIC models can be used to control for sociodemographic or other types of covariates in CFA and more general SEM specifications.

Remarque : ne marche qu'avec les covariates exogènes de moins de 2 facteurs (à transformer en indicatrices j'imagine)

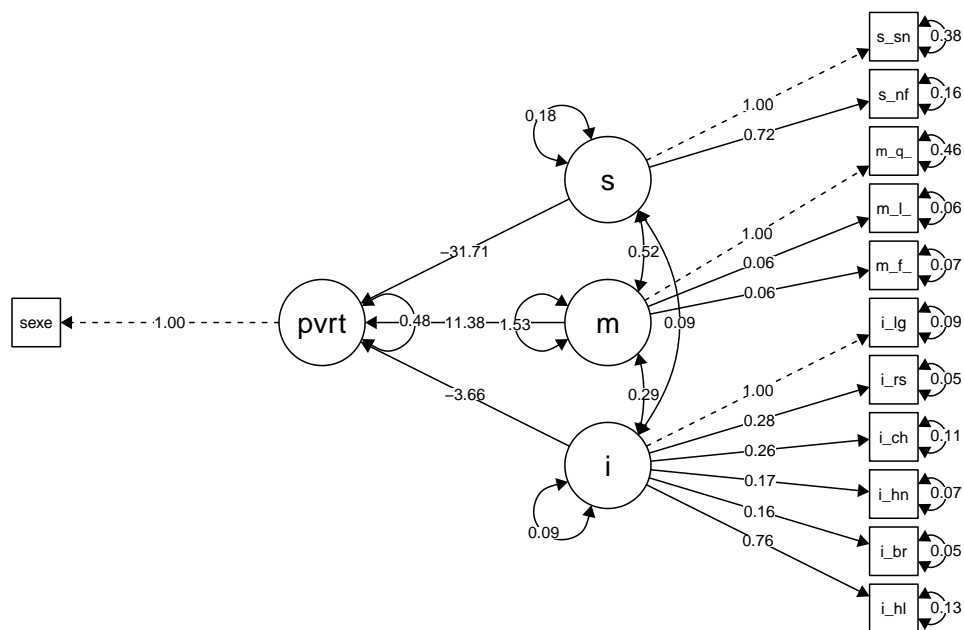


3.6 Structural equation models (SEM)

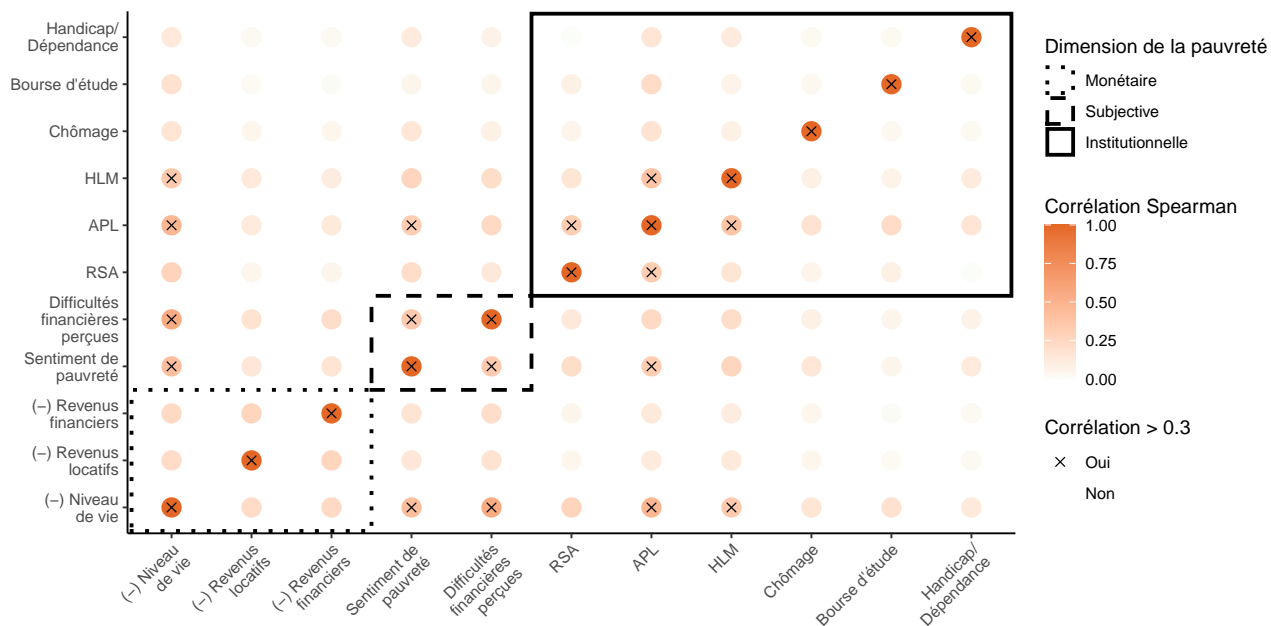
Structural equation models (SEM) integrate confirmatory factor analysis (CFA) into a larger path analytic framework. Formally, we extend the basic CFA expression (measurement model) by an additional linear specification reflecting dependencies among the latent variables (structural model).

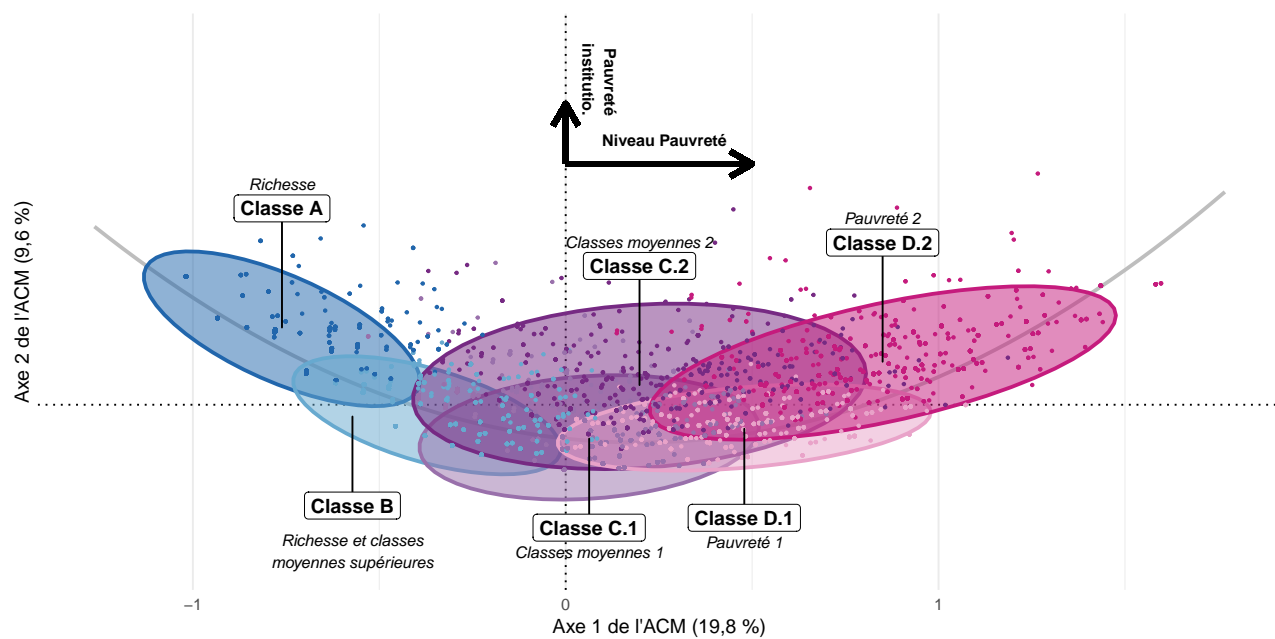
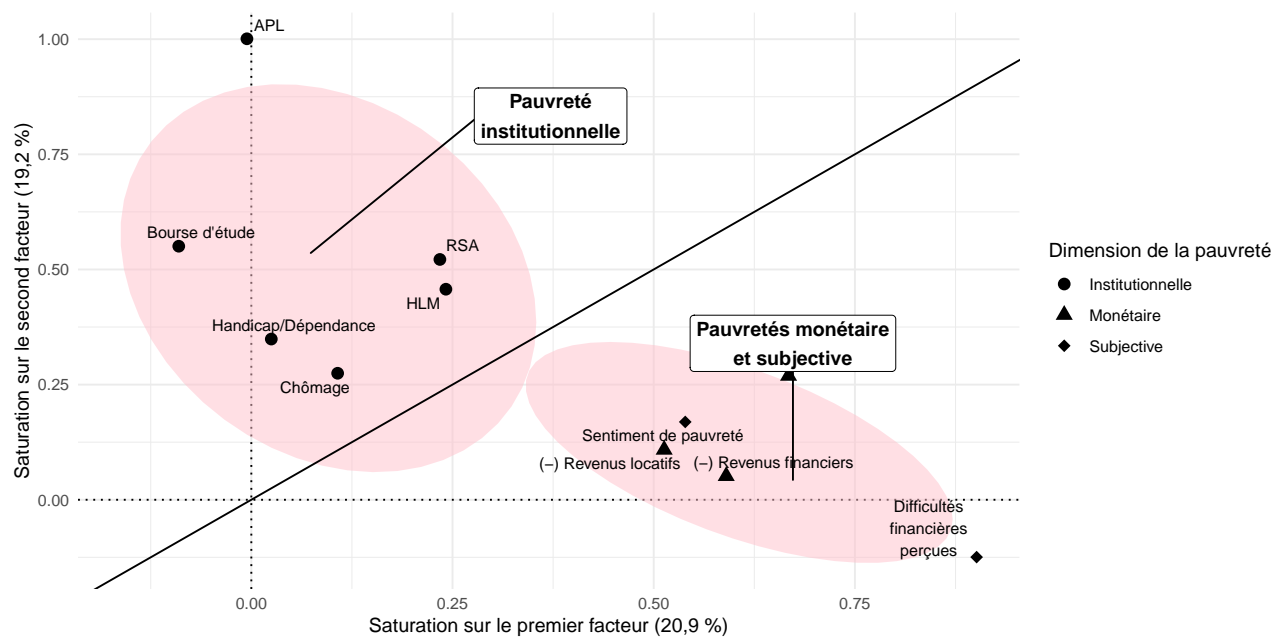
Remarque : ne marche pas pour les facteurs non ordonnés (en gros, considère les facteurs comme des variables numériques)

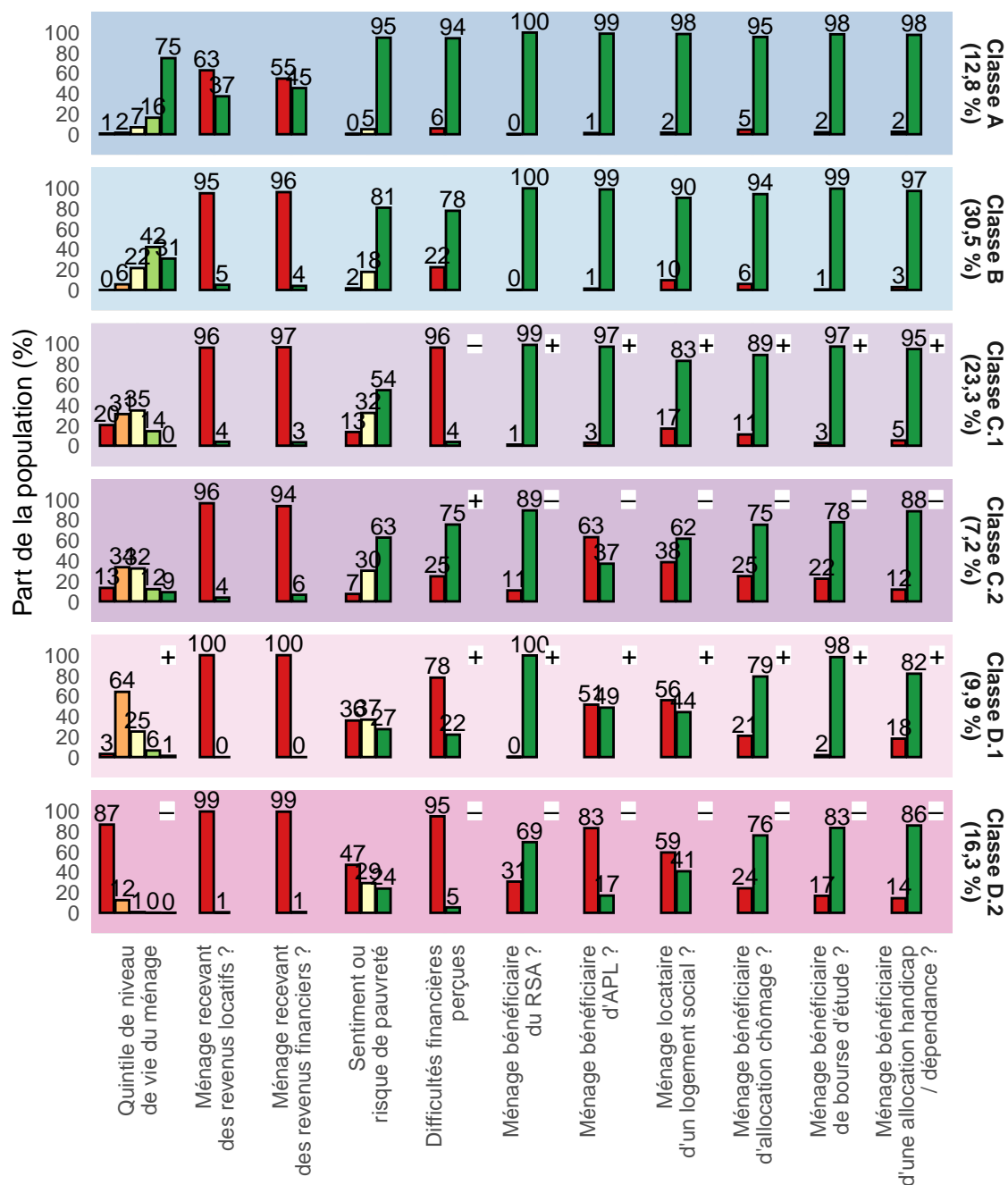
Remarque : estimator ML for ordered data is not supported yet. Use WLSMV instead.



3.7 Figures rapport







4 Notes méthodologiques

Pour ces modèles cinq vagues du Baromètre ont été empliées : 2015, 2016, 2017, 2018 et 2019 (15 137 observations). Le nombre d'observations utilisées est différent dans chaque modèle, il s'agit uniquement des individus où toutes les variables utilisées dans les modèles sont renseignées (voir notes en bas des tableaux).

Bibliographie

- <https://stats.idre.ucla.edu/spss/seminars/efa-spss/> <https://support.sas.com/resources/papers/proceedings/proceedings/sugi30/203-30.pdf> <https://community.jmp.com/t5/JMP-Blog/Principal-components-or-factor-analysis/ba-p/38347> bases de l'EFA
- En bouquins : https://books.google.es/books?hl=fr&lr=&id=qKrumJ4CsboC&oi=fnd&pg=PT180&ots=TDmmzvQP5X&sig=7gFjzxbPC49Tz7IkGT-4gXMzx8U&redir_esc=y#v=onepage&q&f=false et slides <https://slideplayer.com/slide/5080/>
- <https://m-clark.github.io/posts/2020-04-10-psych-explained/>
- <https://cran.r-project.org/web/packages/psychTools/vignettes/factor.pdf>
- https://rstudio-pubs-static.s3.amazonaws.com/363499_73a1c1a94da148b6ad81e6eb8dc1b771.html
- https://en.wikipedia.org/wiki/Factor_analysis
- Analyse en facteurs communs et spécifiques docs en Français. <https://www.rocq.inria.fr/axis/modulad/archives/numero-37/Chaventetal-37/Chaventetal-37.pdf> <http://grumlidesforets.free.fr/cours%20psycho/M1%20psycho/chapitre2/chapitre2.pdf> http://jeanalain.monfort.free.fr/Dicostat2005/A/Analyse_en_facteurs_communs_etc.pdf <https://www.google.com/url?sa=t&rct=j&q=&esrc=s&source=web&cd=&ved=2ahUKEwjX-NWssbbxAhUNxoUKHXMzBxEQFnoECAkQAA&url=http%3A%2F%2Fwww.normalesup.org%2F~carpentier%2FNotes%2FAnalyse-factorielle%2FAnalyse-Factorielle-2011.doc&usg=AOvVaw04RfWMowmry0JRVMNZqR7h> http://jeanalain.monfort.free.fr/Dicostat2005/A/Analyse_en_facteurs_communs_etc.pdf https://www.psychometrie.jlroulin.fr/cours/aide_quizz.html?H.html https://www.persee.fr/doc/hism_0982-1783_1997_num_12_3_1544 <http://psychologie.psyblogs.net/2012/01/cours-theories-de-lintelligence-en.html>