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A Scale for Markets and Property in the Societies of the Standard Cross-Cultural Sample: a Linear Programming Approach[1]

E. Anthon Eff *
Middle Tennessee State University, Murfreesboro, TN

Abstract

Cross-cultural researchers often combine several component variables into a composite index or "scale." The value of a scale for a particular observation is sensitive not only to the values of its component variables, but also to the values of the weights used to combine the components. This sensitivity to weight values is unfortunate, given that the choice of weighting scheme is in some ways arbitrary. A method is presented here, based on linear programming, which reduces the sensitivity of a scale to the component weights. An example scale is produced, for the prevalence of markets and property rights in the societies of the Standard Cross-Cultural Sample. A program, written for R, is included.

Key words: Standard cross-cultural sample; linear programming; Tiered Data Envelopment Analysis; market and property rights index

JEL category: Z13, C6

*E. Anthon Eff, Associate Professor, Department of Economics and Finance, Middle Tennessee State University, Murfreesboro, TN 37132, phone: 615-898-2387, fax: 615-898-5045, email: eaeff@mtsu.edu

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I. Introduction

Cross-cultural researchers often produce "scales" in which the values of several variables are combined into a composite index. In the Standard Cross-Cultural Sample (SCCS), a scale is most often simply the sum of the component variables as, for example, the cultural complexity scale formed by summing variables 149 through 158 (Murdock and Provost 1971); the pathogen stress scale (variable 1260) formed by adding variables 1253 through 1259 (Low 1988); and the modernization scale (variable 1849) created by summing variables 1806 through 1838 (Divale and Seda 2000). Other scales are produced using factor analysis, such as the factors produced on the gossip-related variables 1781-1805 (Divale and Seda 1999).

Scales created by summing component variables, by principal components analysis, or by factor analysis are all examples of composite indices, in which the values of component variables are combined into a single ordinal scale. A composite index, in its most general form, is the weighted sum of the component variables:

$$\theta_i = \sum_{r=1}^{p} y_{ri}\mu_r \quad , \ \forall i \tag{1}$$

where the value of the index for society i (θ_i) is the sum of the component variable values (y_{ri}) for p components, each component value weighted by a weight (μ_r). The component variables are almost always first scaled similarly, typically by standardizing or converting to ranks. A wide variety of methods exist for specifying the weights μ_r, and in most cases, there is no *a priori* reason to choose one weighting scheme over another. The choice of weights can therefore often be criticized as arbitrary.

<Figure 1 about here>

Figure 1a presents a scatter plot of two component variables for 20 societies. Note that society *A* has a low value for component 1 but a very high value for component 2. Society *T* is in the opposite situation: a very high value for component 1 but a low value for component 2. *A* would rank highest with high weights on component 2, and *T* would rank highest with high weights on component 1. Both of these societies would rank relatively low when using equal weights on each component, a scheme which would cause societies *O* and *Q* to rank quite high. One can see, then, that changes in weights can lead to large changes in the overall index.

II. Proposed method

Ideally, one would wish for a method that diminishes the effect of weight choice in ranking societies. The method we describe here does just that: it separates societies into groups, such that the between-group differences in index rank are based solely on data values (y_r), not on weights (μ_r). The method employs linear programming, solving for weights on the individual components (μ_r) in order to calculate the highest possible index for the k^{th} society:

$$\text{Maximize} \qquad \theta_k = \sum_{r=1}^{p} y_{rk}\mu_r \tag{2.a}$$

$$\text{Subject to} \qquad \sum_{r=1}^{p} y_{ri}\mu_r \le 1,\ \forall i \tag{2.b}$$

$$\mu_r \ge 0,\ \forall r \tag{2.c}$$

The constrained maximization problem in equations (2.a)-(2.c) is solved *n* times—once for each of the *n* societies. The objective function (2.a) selects weights in order to maximize the index score of the k^{th} society. Constraint (2.b), however, restricts the weights so that—applied to every one of the *n* societies—no society has a score higher than one. Thus, the highest value that the objective function may take is one—in such a case, the society will lie on the frontier shown in Figure 1a. In all other cases, the value of the objective function will be less than one, since the weights that maximize its own score give another society a score of one. Society *S*'s index score, for example, would equal the solid portion of the ray on which it lies, divided by the total length of the ray below the frontier.

The difference between the frontier and the below-frontier societies is not caused by weights, since there exists no set of weights which can make the below-frontier societies the peers of the frontier societies.

Thus, finding a frontier to which each society belongs (as in Figure 1b) would be a way of grouping societies into subsets *within which* differences in index values can be removed by weight adjustment, and *between which* differences in index values cannot be removed by adjusting weights. This property is attractive, since it allows us to construct an index, consisting of the order of a society's frontier (as in Figure 1b), whose values are not determined by an arbitrary choice of weights.

In practice, one would usually choose to replace the zero in constraint (2.c) with a very small positive number, so that *all* component variables are considered when computing the optimum. The larger the constraint level, the greater the number of frontiers that will be generated. One might also add a constraint so that the *shares* of all component variables in the optimum exceed a certain threshold (Pedraja, et al. 1997).

This method of creating composite indices is closely related to the operations research procedure called *Tiered Data Envelopment Analysis* (TDEA) (Barr, et al. 2000), based on the widely used efficiency analysis technique Data Envelopment Analysis (Charnes, et al. 1978). Whereas TDEA is used to maximize an efficiency *ratio* of outputs over inputs, the present method in effect maximizes only the *numerator* of the efficiency ratio (the outputs). This numerator-only method has previously been used for ranking entities such as elementary schools (Eff 2004), universities (Bougnol and Dulá 2006), and U.S. states (Eff and Eff 2007).

III. A scale for markets and property

As an example of this method, a scale is created for the prevalence of markets and property rights for the 186 societies in the SCCS. Descriptive statistics for the seven component variables selected are given in Table 1; the Pearson correlation coefficients in Table 2; and the SCCS codebook entries for each of these in Appendix 1.

<Table 1 and Table 2 about here>

The large number of missing values in the SCCS makes it prudent to use multiple imputation (Dow and Eff 2009a, 2009b; Eff and Dow 2009). Accordingly 10 imputed data sets are created, each data set containing the seven component variables, with missing values replaced by imputed values. A scale is computed separately for each of the 10 imputed data sets.

The seven component variables are selected from a larger number which plausibly provide some measure of the prevalence of markets and property rights. Unlike scales based on shared variation, candidate variables for the TDEA scale need not be strongly correlated with each other—the suitability of a candidate variable is determined *conceptually* ("does this variable measure some dimension of what this scale tries to capture?") rather than *empirically* ("does this variable correlate strongly with the other variables?"). Thus, for example, TDEA rankings of secondary schools might include component variables that are nearly orthogonal with each other, such as academic scores and the performance of sports teams. Despite the lack of shared variation, these nearly orthogonal variables measure valid dimensions of what one would consider a high school's performance, and so are conceptually sound choices for component variables.

Nevertheless, most scales used in cross-cultural research would in fact contain component variables that correlate *consistently* with each other—that is, the correlations of a component with other components would all be of the same sign and usually significant. From Table 2, one can see that the seven selected variables all have consistently signed correlations, though the Cronbach's alpha (0.653) would be considered a little low for scales based on shared variation, such as principal components or factor analysis. In fact, one can imagine that factor analysis might produce two latent variables from these seven component variables: one for markets, another for property. A virtue of the TDEA approach is that separate, but related, dimensions can be combined into a composite index.

An R program

Appendix 2 presents an R program that creates 10 imputed data sets and then calculates the scale for each set of data. The program, as well as the two data files it calls, is available online, in a zip folder.[2] The user should unzip the zip folder, and change the working directory in the R program to the name of the folder where the zip folder was unzipped.

Higher values for each variable should have similar conceptual meanings. In this case, higher values should all indicate greater development of property rights and markets. As Table 2 shows, one of our variables (v1726) correlates negatively with the remaining six: higher values indicate *less* private property, not more. This variable is therefore multiplied by negative one, to ensure that it varies directly with the others.

Ten imputed data sets are created, using the auxiliary data set described in Eff and Dow (2009). All seven component variables are then standardized, with a mean of 100 and a standard deviation of 15, so that no values are negative. The standardizations are performed separately within each of 10 imputed data sets.

The following section of code executes a series of nested loops, finding the optimal weights for each society, one imputed data set at a time. Within each imputed data set, any society reaching the frontier is removed from the set of comparison societies, until all societies have been removed. The order of removal indicates a society's rank, and is recorded as the field *`iter`* in the dataframe *`sx`*. The order of removal is then inverted to create the desired scale: *`sx$iter<-(max(sx$iter)+1)-sx$iter`*.

Two output files are produced. The file *`R_WCtable.csv`* presents a table of the results, with society names, so that one can look over the rankings in a spreadsheet. The file *`findat.Rdata`* arranges the data so that it can be most easily used in a regression, using the programs given in Eff and Dow (2009).

[2] http://frank.mtsu.edu/~eaeff/downloads/LP scales in R.zip

The program sets the minimum weight size in constraint (2.c) to one-millionth, in the line reading `bvec[1:NROW(fc)]<-(1/10^6)`. Were one to set this level to an even smaller number, fewer discrete values would appear in the final scale. For the current example, a minimum weight size of one-billionth returned six discrete values; a size of one-trillionth returned three discrete values.

Appendix 3 shows the values for the scale for each of the 10 imputations, sorted in ascending order for the society mean. The table is presented simply to show that the resulting scale seems reasonable, given the societies that rank low and high. The mean scale should not be used in a regression analysis, since it contains imputed values; a regression analysis should be conducted on each of the imputed data sets, and the results combined, as shown in Dow and Eff (2009a, 2009b) and in Eff and Dow (2009).

When the component variables are highly correlated with each other, the TDEA scale will be quite similar to the first principal component of the variables. Since the first principal component in such cases will have nearly equal weights on each of the variables, the mean or sum of the variables would also correlate quite highly with the first principal component (since these are also equal-weight indices). For our market and property index, with moderate correlation among the seven variables, the first principal component and the mean are practically identical, with a correlation of 0.992. The correlation between the TDEA scale and these two measures is about 0.793—quite high, but still different. This shows that allowing weights to vary, so as to group societies for which weight adjustments suffice to produce identical outcomes, leads to non-trivial differences in the ordinal ranking of societies.

IV. Summary

The scales often used by cross-cultural researchers are weighted sums of component variables. Different choices of weights will produce different rank orderings of societies. The method presented here reduces the sensitivity of the scale to the weights chosen, by classifying together societies for whom adjustments in weights give an equally high rank.

The method is particularly suitable for cases where weakly correlated or orthogonal variables are combined into a scale. For example, variables for internal war and external war (Ember and Ember 1992) could be combined into a scale for the prevalence of war.

The R program given in Appendix 2 creates a scale for the prevalence of markets and property rights in the 186 societies of the SCCS, using the seven component variables shown in Appendix 1. Since multiple imputation offers the best approach for using the SCCS (Dow and Eff 2009a, 2009b), the program creates the scale for each of 10 imputed data sets. With suitable modifications, the program can be used to produce any scale for SCCS data.

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Table 1: Descriptive statistics for component variables

Variable	Label	N	Max	Mean	Min	invert	Alpha
v17	Money Media Of Exchange And Credit	183	5	2.617	1	0	0.570
v1726	Communality Of Land	98	1	2.240	3	1	0.624
v1732	Presence Of Wage Labor	89	2	1.603	1	0	0.637
v1733	Market Exchange Within Local Community	96	4	2.792	1	0	0.648
v1734	Market Exchange Outside Of Local Community	99	4	3.426	1	0	0.640
v278	Inheritance Of Real Property (Land)	155	2	1.596	1	0	0.595
v279	Inheritance Of Movable Property	152	2	1.821	1	0	0.601
TDEAscale	Scale produced from GAMS program	186	12	7.11	1		

Notes: All variables are from the SCCS. Cronbach's alpha=0.653. "Alpha" is the Cronbach's alpha when the row variable is *excluded*. "invert"=1 when the variable is negatively correlated with the meaning of the scale. The descriptive statistics and the alphas are all produced from multiply imputed data (*m*=10).

Table 2: Pearson correlation coefficients among component variables

Variable	v17	v1726	v1732	v1733	v1734	v278	v279	mnAbs
v17	1.00	-0.35	0.25	0.21	0.21	0.42	0.29	0.39
v1726	-0.35	1.00	-0.17	-0.11	-0.14	-0.31	-0.13	0.31
v1732	0.25	-0.17	1.00	0.12	0.14	0.14	0.24	0.29
v1733	0.21	-0.11	0.12	1.00	0.22	0.11	0.17	0.28
v1734	0.21	-0.14	0.14	0.22	1.00	0.11	0.20	0.29
v278	0.42	-0.31	0.14	0.11	0.11	1.00	0.42	0.36
v279	0.29	-0.13	0.24	0.17	0.20	0.42	1.00	0.35

Notes: Variable labels given in Table 1. "mnAbs" is the mean of the absolute values of the row correlation coefficients.

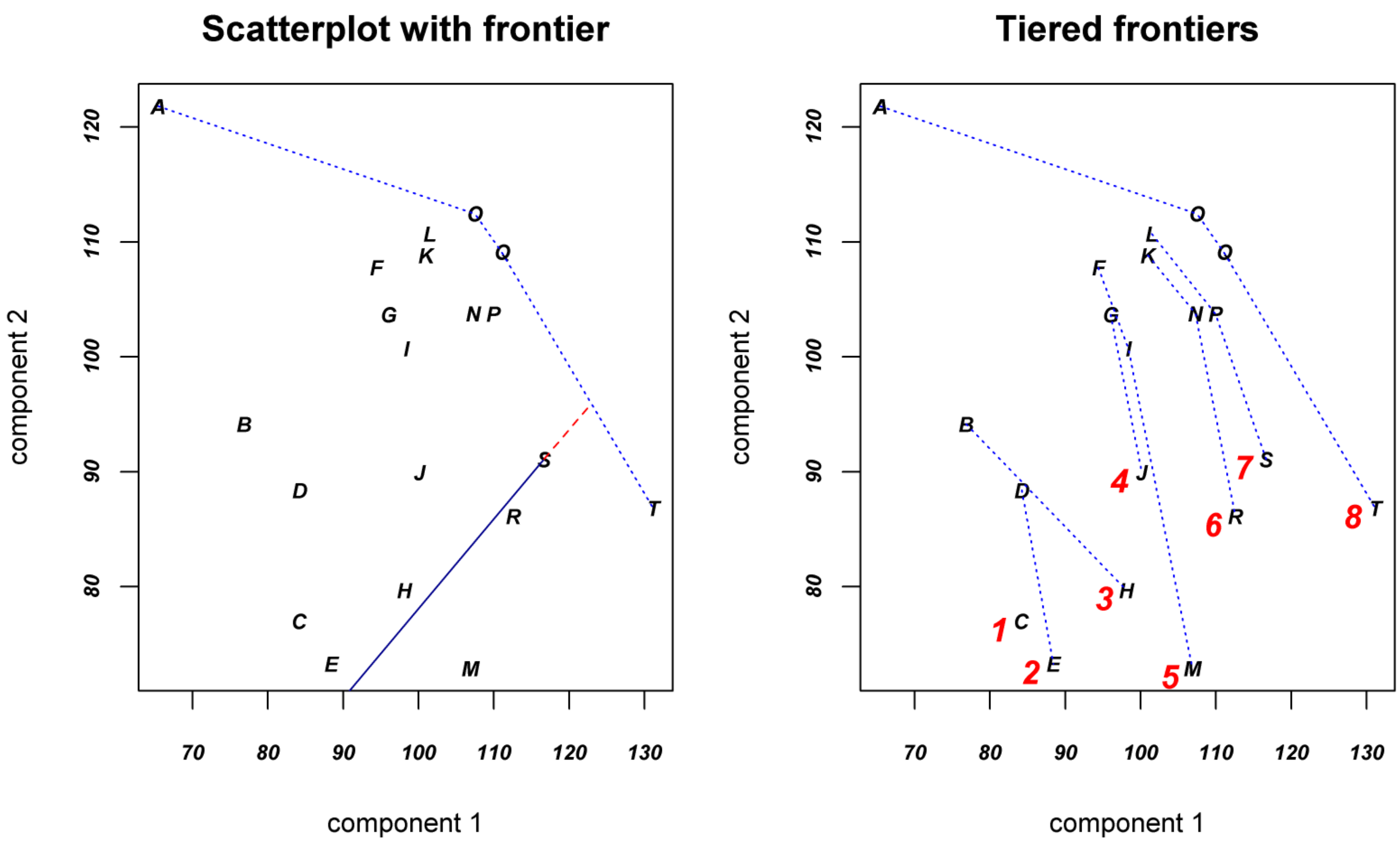

Figure 1: The values of two component variables are plotted for twenty societies. Linear programming is used to wrap a convex frontier around the cloud of points; societies on the frontier are tied for the highest composite score, while societies below the frontier have a score given by their location as the proportion of the distance from the origin to the frontier. The tiered frontiers method draws a series of successive convex frontiers, classifying each society into a peer group, based on the values of the component variables. The order of the frontier is then used as an index.

Appendix 1: Variable descriptions from the SCCS (Divale 2004)

```
17.  Money (media of exchange) and credit
      3    . = Missing Data
     77    1 = No media of exchange or money
     12    2 = Domestically usable articles as media of exchange
     26    3 = Tokens of conventional value as media of exchange
     42    4 = Foreign coinage or paper currency
     26    5 = Indigenous coinage or paper currency

278.  Inheritance of real property (land)
279.  Inheritance of movable property
       *   Note change in order from 278 280              278   279
                                                          Land  Movables
       . = Missing data                                    31    34
       1 = Absence of individual property rights or rules   59    22
       2 = Matrilineal (sister's sons)                      4     5
       3 = Other matrilineal heirs (e.g., younger brothers)  9     9
       4 = Children, with daughters receiving less         12    14
       5 = Children, equally for both sexes                 9    22
       6 = Other patrilineal heirs (e.g., younger brothers)  8     9
       7 = Patrilineal (sons)                              54    71

1726. Communality of land
     88    . = missing data
     22    1 = land predominantly private property
     24    2 = land partially communally used
     52    3 = communal land use rights only

1732.  Presence of wage labor
     97    . = missing data
     36    1 = no wage labor
     22    2 = wage labor present, migratory labor unimportant
     31    3 = wage labor, mainly in the form of migratory labor

1733.  Market exchange within local community
     90    . = missing data
     23    1 = no market exchange (original code 10)
     10    2 = market exchange within local community present, no
           *   further information (original code 20)
     27    3 = market exchange within local community present, involving
           *   local and regional products (original code 21)
     36    4 = market exchange within local community present, involving
           *   local, regional, and supra-regional products (original
           *   code 22)

1734.  Market exchange outside of local community
     87    . = missing data
     10    1 = no market exchange outside of local community
           *   (original code 10)
      5    2 = market exchange outside of local community (at trading
           *   posts, market places), no further information (original
           *   code 20)
     26    3 = market exchange outside of local community, involving
           *   local and regional products (original code 21)
     58    4 = market exchange outside of local community, involving
           *   local, regional, and supra-regional products (original
           *   code 22)
```

Appendix 2: R program for producing LP scales

```
#--make imputed datasets, calculate LP scales--
#-- for more info on multiple imputation see http://escholarship.org/uc/item/7cm1f10b

#--make imputed datasets, calculate LP scales--
#--see http://escholarship.org/uc/item/7cm1f10b for multiple imputation

#--change the following path to the directory with your data and program--
setwd("d:/projects/MI")
rm(list=ls(all=TRUE))
options(echo=TRUE)
#--you need the following packages--you must install them first--
library(foreign)
library(mice)
library(vegan)
library(linprog)
library(psych)

#--To find the citation for a package, use this function:---
citation("linprog")

#--Read in auxiliary variables---
load("vaux.Rdata",.GlobalEnv)
row.names(vaux)<-NULL
#--Read in the SCCS dataset---
load("SCCS.Rdata",.GlobalEnv)
#--check to see that rows are properly aligned in the two datasets--
#--sum should equal 186---
sum((SCCS$socname==vaux$socname)*1)
#--remove the society name field from vaux--
vaux<-vaux[,-28]
names(vaux)

#--list variables for your scale--
capi<-SCCS[,c("v17","v1726","v1732","v1733","v1734","v278","v279")]
#--invert those that need inverting--
capi[,"v1726"]<-capi[,"v1726"]*(-1)

#--look at your data: correlation matrix, moment stats, and Cronbach's alpha
cor(capi,use="pair")
describe(capi)
alpha(capi)

#----Multiple imputation------
#--number of imputed data sets to create--
nimp<-10
zxx<-data.frame(cbind(vaux,capi))
v<-complete(mice(zxx,maxit=20,m=nimp),action="long")
vnn<-names(capi)
v<-v[,c(vnn,".id",".imp")]

#--standardize each variable in each data set (m=100,s=15)---
for (i in 1:max(v$.imp)){
v[which(v$.imp==i),vnn]<-decostand(v[which(v$.imp==i),vnn],"standardize")*15+100
}

#---Tiered DEA scales--------
#--Create two output files--one to view the resulting scales,
#--the other to use when estimating a regression model---

key<-SCCS[,c("sccs#","socname")]
names(key)[1]<-".id"
key<-key[order(key$.id),]
findat<-NULL

for (imn in 1:max(v$.imp)){
z1<-which(v$.imp==imn)
Amat<-as.matrix(v[z1,vnn])
row.names(Amat)<-v$.id[z1]
pnv<-row.names(Amat)
```

```
fc<-matrix(0,NCOL(Amat),NCOL(Amat))
diag(fc)<-1
rownames(fc)<-paste("ct",(1:NCOL(Amat)),sep="")
colnames(fc)<-colnames(Amat)
Amat<-rbind(fc,Amat)
sx<-NULL
iter<-0
o<-pnv
while (length(o)>1){
dea<-NULL
iter<-iter+1
bvec<-rep(1,NROW(Amat))
#--below is lower threshold for each weight--can make as low as 1/10^9--
bvec[1:NROW(fc)]<-(1/10^6)
names(bvec)<-rownames(Amat)
f.dir<-rep(c(">=","<="),c(NROW(fc),length(o)))
for (i in 1:length(o)){
cvec<-(Amat[o[i],])
olp<-lp("max", cvec, Amat, f.dir, bvec)
dea<-rbind(dea,olp$objval)
}
z<-which(round(dea[,1],7)==1)
sx<-rbind(sx,cbind(data.frame(o[z]),iter))
z<-which(round(dea[,1],7)!=1)
o<-o[z]
if (length(o)>=1){Amat<-Amat[c(rownames(fc),o),]}
}
names(sx)[1]<-".id"
sx$iter<-(max(sx$iter)+1)-sx$iter
key<-merge(key,sx,by=".id",all=TRUE)
names(key)[NCOL(key)]<-paste("M",imn,sep="")
gx<-v[z1,c(".id",".imp",vnn)]
gx<-merge(gx,sx,by=".id")
findat<-rbind(findat,gx)
}


#--look at what you got--
dim(key)
key$mean<-apply(key[,3:12],1,mean)
head(key[order(key$mean),])
tail(key[order(key$mean),])

#--write to file--
write.csv(key,"R_WCtable.csv")

#--data to use in regression model--
head(findat)
save(file="findat.Rdata")
```

Appendix 3: Markets and Property scale for the 10 imputed data sets

.id	socname	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	mean
173	Siriono	1	1	1	1	1	1	1	1	1	1	1
180	Aweikoma	1	1	1	1	1	1	1	1	1	1	1
179	Shavante	1	1	1	4	1	1	1	4	1	3	1.8
79	Andamanese	3	3	2	1	4	1	1	2	1	1	1.9
2	Kung Bushmen	3	3	2	2	3	3	2	3	3	2	2.6
98	Trobrianders	5	3	2	2	4	5	2	4	5	4	3.6
163	Yanomamo	4	4	4	4	3	3	2	4	3	5	3.6
186	Yahgan	3	2	3	5	3	4	3	5	4	4	3.6
92	Orokaiva	2	2	4	3	1	7	2	5	6	5	3.7
178	Botocudo	4	4	6	5	2	3	1	2	6	7	4
182	Lengua	4	7	2	4	4	2	4	3	8	4	4.2
176	Timbira	4	6	4	2	6	9	5	6	4	3	4.9
183	Abipon	6	7	4	5	8	2	2	5	2	8	4.9
170	Amahuaca	10	3	8	2	4	2	6	3	10	4	5.2
181	Cayua	5	4	5	7	6	5	7	1	9	3	5.2
137	Paiute (North.)	9	4	6	2	2	5	2	8	5	10	5.3
164	Carib (Barama)	6	10	3	6	4	10	2	3	3	7	5.4
133	Twana	6	5	6	4	6	7	4	5	5	7	5.5
162	Warrau	5	5	8	5	6	5	2	5	8	6	5.5
91	Aranda	5	5	5	5	5	8	4	6	6	7	5.6
175	Trumai	6	4	5	6	5	6	4	7	7	7	5.7
140	Gros Ventre	7	7	6	6	8	7	3	4	4	7	5.9
25	Pastoral Fulani	5	5	7	5	6	7	4	5	8	8	6
104	Maori	7	4	5	4	7	8	4	7	7	7	6
174	Nambicuara	5	4	7	9	5	4	6	6	8	6	6
9	Hadza	8	8	3	4	6	6	7	8	5	7	6.2
130	Eyak	8	7	5	6	5	8	6	6	6	6	6.3
138	Klamath	4	7	9	6	3	7	5	2	10	10	6.3
148	Chiricahua	11	6	9	3	8	3	6	7	5	5	6.3
185	Tehuelche	6	6	6	7	7	8	6	5	10	3	6.4
96	Manus	8	5	7	6	7	9	3	6	6	8	6.5
120	Yukaghir	4	4	4	7	14	10	4	5	9	6	6.7
129	Kaska	7	6	6	6	6	9	5	7	7	8	6.7
166	Mundurucu	6	5	7	6	6	7	5	7	8	10	6.7
165	Saramacca	8	5	7	7	6	8	4	8	7	8	6.8
41	Tuareg	7	7	6	6	7	9	5	7	7	8	6.9
157	Bribri	8	10	6	3	7	6	4	4	11	10	6.9
13	Mbuti	6	6	8	6	7	8	5	6	9	9	7
24	Songhai	8	9	3	6	8	11	5	5	9	6	7
31	Shilluk	8	6	4	6	9	10	3	6	9	10	7.1
90	Tiwi	5	7	8	8	8	9	5	6	6	9	7.1
147	Comanche	6	6	6	7	7	8	5	9	6	11	7.1
161	Callinago	6	3	10	7	9	13	3	8	9	3	7.1
4	Lozi	8	5	6	6	9	9	6	8	8	8	7.3
124	Copper Eskimo	5	7	8	6	4	10	9	9	4	11	7.3
19	Ashanti	8	6	8	7	7	8	5	8	8	9	7.4
6	Suku	8	6	7	7	8	9	5	8	8	9	7.5
99	Siuai	8	5	8	6	10	9	5	6	9	10	7.6
177	Tupinamba	7	8	6	8	9	5	4	9	11	9	7.6
128	Slave	8	8	10	6	7	11	6	6	6	9	7.7
86	Badjau	8	5	7	8	9	7	6	9	9	10	7.8
139	Kutenai	8	6	8	7	8	9	6	8	8	10	7.8
30	Otoro Nuba	10	8	7	5	7	10	6	8	10	8	7.9

.id	socname	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	mean
141	Hidatsa	7	7	7	8	7	10	7	9	8	9	7.9
7	Bemba	13	9	6	7	6	8	5	10	6	11	8.1
27	Massa (Masa)	9	7	7	4	11	10	4	14	9	6	8.1
77	Semang	7	7	9	8	7	9	6	8	9	11	8.1
8	Nyakyusa	9	7	8	8	8	9	6	9	9	9	8.2
97	New Ireland	7	7	12	8	11	10	7	7	5	8	8.2
103	Ajie	8	7	8	8	8	10	6	9	9	9	8.2
146	Natchez	11	7	7	7	11	11	4	11	7	6	8.2
10	Luguru	9	10	7	5	6	10	7	10	8	11	8.3
70	Lakher	9	8	8	7	10	8	6	8	8	11	8.3
134	Yurok	8	8	10	7	9	10	5	8	8	10	8.3
142	Pawnee	7	7	9	8	8	9	6	9	9	11	8.3
121	Chukchee	7	7	9	8	11	9	6	7	10	10	8.4
131	Haida	10	8	5	3	8	12	7	12	9	10	8.4
168	Cayapa	8	9	10	7	3	6	10	9	13	9	8.4
100	Tikopia	9	8	8	7	8	10	7	9	9	10	8.5
5	Mbundu	9	6	8	9	8	11	9	8	10	8	8.6
40	Teda	9	6	9	8	9	9	8	8	8	12	8.6
1	Nama Hottentot	8	9	8	7	10	10	8	8	7	12	8.7
22	Bambara	9	7	9	8	9	10	6	9	10	10	8.7
52	Lapps	10	8	9	8	5	10	8	10	8	11	8.7
169	Jivaro	7	8	9	8	9	10	7	9	9	11	8.7
101	Pentecost	8	8	8	12	9	9	5	7	10	12	8.8
111	Palauans	9	8	9	8	9	10	7	9	9	10	8.8
126	Micmac	8	8	9	9	9	9	8	10	9	9	8.8
143	Omaha	10	7	9	9	6	11	7	8	10	11	8.8
135	Pomo (Eastern)	9	8	9	8	9	10	7	9	9	11	8.9
29	Fur (Darfur)	9	8	9	8	10	10	7	9	9	11	9
61	Toda	9	8	10	8	9	10	7	9	9	11	9
89	Alorese	9	7	11	5	9	11	7	11	8	12	9
127	Saulteaux	12	9	8	9	8	9	6	8	12	10	9.1
12	Ganda	9	8	9	9	9	11	7	10	10	10	9.2
64	Burusho	11	10	5	11	12	12	10	7	10	4	9.2
35	Konso	13	8	8	8	12	10	7	8	11	8	9.3
72	Lamet	9	8	10	9	9	11	7	9	10	11	9.3
93	Kimam	9	11	9	9	9	9	5	13	7	12	9.3
123	Aleut	9	9	10	8	10	10	6	10	10	11	9.3
136	Yokuts (Lake)	10	8	11	7	10	11	6	9	10	11	9.3
55	Abkhaz	9	7	7	10	11	13	8	11	8	10	9.4
74	Rhade	11	7	12	7	11	9	8	10	7	12	9.4
102	Mbau Fijians	7	9	9	7	9	11	8	12	10	12	9.4
39	Kenuzi Nubians	11	11	8	9	11	8	6	7	11	13	9.5
69	Garo	10	9	11	9	9	10	7	9	10	11	9.5
109	Trukese	9	8	9	9	11	12	7	10	10	10	9.5
132	Bellacoola	9	9	9	9	10	11	7	10	10	11	9.5
150	Havasupai	10	10	10	8	10	10	6	11	9	11	9.5
11	Kikuyu	10	9	9	9	9	11	8	10	10	11	9.6
16	Tiv	10	9	10	8	10	11	7	10	10	11	9.6
36	Somali	10	9	11	8	9	11	7	10	10	11	9.6
60	Gond	12	9	11	6	10	10	8	8	11	11	9.6
87	Toradja	11	5	9	8	10	15	8	7	10	13	9.6
112	Ifugao	8	11	11	8	11	11	8	10	8	10	9.6
125	Montagnais	9	9	10	9	11	11	7	9	10	11	9.6
81	Tanala	9	9	10	10	11	11	7	9	9	12	9.7
107	Gilbertese	8	7	11	8	12	10	9	12	9	11	9.7

.id	socname	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	mean
159	Goajiro	9	10	12	9	9	11	6	10	10	11	9.7
118	Ainu	9	9	10	9	10	11	8	10	10	12	9.8
167	Cubeo (Tucano)	9	9	10	9	10	11	8	10	10	12	9.8
34	Masai	10	9	8	9	11	12	8	10	10	12	9.9
184	Mapuche	10	9	10	9	10	11	8	10	11	11	9.9
21	Wolof	10	9	10	10	10	12	7	10	11	11	10
105	Marquesans	11	11	12	9	12	11	8	8	10	8	10
119	Gilyak	10	9	11	9	10	11	8	10	10	12	10
26	Hausa	9	10	9	10	10	12	8	11	11	11	10.1
152	Huichol	12	7	11	8	11	11	7	10	12	12	10.1
33	Kaffa (Kafa)	11	7	10	10	11	12	5	11	12	13	10.2
73	Vietnamese	11	12	8	10	11	11	6	9	12	12	10.2
32	Mao	11	8	11	7	11	12	9	11	10	13	10.3
53	Yurak Samoyed	10	9	10	11	10	12	8	11	11	11	10.3
58	Basseri	9	9	11	9	11	12	8	11	11	12	10.3
106	Western Samoans	8	11	13	12	11	11	7	9	12	9	10.3
155	Quiche	14	11	10	9	9	10	7	11	12	10	10.3
171	Inca	6	11	10	13	10	13	6	10	12	12	10.3
110	Yapese	10	10	11	10	11	11	8	11	10	12	10.4
145	Creek	11	9	10	10	11	12	8	10	11	12	10.4
17	Ibo	12	9	12	7	8	12	9	11	11	14	10.5
172	Aymara	11	9	10	10	11	12	8	11	11	12	10.5
23	Tallensi	11	10	11	9	11	12	8	11	11	12	10.6
65	Kazak	10	11	9	10	10	12	8	12	12	12	10.6
71	Burmese	11	10	11	10	11	11	8	11	11	12	10.6
82	Negri Sembilan	11	10	11	11	9	12	10	10	10	12	10.6
122	Ingalik	11	10	11	9	11	12	8	11	11	12	10.6
144	Huron	10	10	10	9	12	11	8	12	11	13	10.6
149	Zuni	11	10	10	10	11	12	9	10	11	12	10.6
151	Papago	11	12	10	8	11	12	7	13	11	11	10.6
20	Mende	10	13	10	10	11	11	9	11	10	12	10.7
57	Kurd	11	10	11	10	11	12	8	11	11	12	10.7
80	Vedda	11	10	11	10	11	12	8	11	11	12	10.7
67	Lolo	11	10	13	11	10	12	8	10	11	12	10.8
85	Iban	12	10	11	10	11	12	8	11	11	12	10.8
88	Tobelorese	10	10	12	10	10	12	8	11	11	14	10.8
154	Popoluca	12	11	12	9	11	9	6	9	14	15	10.8
158	Cuna (Tule)	13	8	12	9	12	11	11	10	11	12	10.9
3	Thonga	11	10	12	10	11	12	9	11	11	13	11
15	Banen	10	11	9	10	12	11	10	13	12	13	11.1
46	Rwala Bedouin	11	10	12	11	11	12	9	11	11	13	11.1
18	Fon	12	11	11	11	10	12	9	12	11	13	11.2
28	Azande	12	11	11	10	12	12	9	12	11	12	11.2
37	Amhara	11	10	11	10	12	13	9	12	12	12	11.2
38	Bogo	12	11	11	10	11	12	10	10	11	14	11.2
56	Armenians	9	12	13	9	13	12	9	12	12	13	11.4
108	Marshallese	12	11	12	11	12	12	9	11	12	12	11.4
49	Romans	10	10	12	11	12	12	9	14	12	13	11.5
54	Russians	12	10	13	11	11	12	9	13	12	12	11.5
95	Kwoma	12	10	11	11	12	13	9	12	12	13	11.5
115	Manchu	13	12	12	12	13	13	8	8	12	12	11.5
153	Aztec	12	10	11	11	12	13	9	12	12	13	11.5
83	Javanese	13	11	12	11	12	14	7	11	11	14	11.6
50	Basques	12	11	12	11	12	13	9	12	12	13	11.7
59	Punjabi (West)	12	11	12	11	12	13	9	12	12	13	11.7

.id	socname	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	mean
62	Santal	12	11	12	11	12	13	9	12	12	13	11.7
113	Atayal	13	9	12	10	13	13	11	11	13	12	11.7
156	Miskito	12	10	13	11	12	13	9	11	12	14	11.7
68	Lepcha	12	12	12	11	13	13	8	13	12	13	11.9
14	Nkundo Mongo	12	12	13	12	13	12	11	13	11	14	12.3
44	Hebrews	14	12	12	11	13	12	10	15	11	13	12.3
76	Siamese	11	11	13	13	14	14	9	13	12	13	12.3
75	Khmer	13	12	13	11	13	14	10	13	13	13	12.5
78	Nicobarese	12	12	14	12	13	14	11	13	12	12	12.5
94	Kapauku	13	12	12	12	12	14	10	13	13	14	12.5
160	Haitians	13	12	13	12	13	13	10	12	13	14	12.5
48	Gheg Albanians	13	12	12	12	12	14	10	15	13	13	12.6
42	Riffians	13	12	13	12	13	14	10	13	13	14	12.7
47	Turks	13	12	13	12	13	14	10	13	13	14	12.7
66	Khalka Mongols	13	12	13	12	13	14	10	13	13	14	12.7
84	Balinese	12	12	14	11	15	14	12	13	13	14	13
45	Babylonians	12	13	13	12	15	13	11	15	13	14	13.1
43	Egyptians	14	13	14	12	13	14	11	13	14	15	13.3
63	Uttar Pradesh	13	13	12	13	15	14	10	14	15	15	13.4
51	Irish	14	13	14	13	14	15	11	14	14	15	13.7
114	Chinese	14	13	14	13	14	15	11	14	14	15	13.7
116	Koreans	14	13	14	13	14	15	11	14	14	15	13.7
117	Japanese	15	14	15	14	15	16	12	15	15	16	14.7